PhD THESIS DECLARATION

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Entrepreneurship in the Making: Understanding Experimentation in Early-Stage Entrepreneurial Firms

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DECLARE

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Abstract

Despite the widespread use of experimental activities in early-stage entrepreneurship, we lack an understanding of how they contribute to the process of new venture creation. I therefore examine experimentation in three different but related empirical settings in my dissertation. First, by analysing experimentation and planning related activities described by entrepreneurs on Kickstarter, the largest crowdfunding platform for creative projects, I find that resource providers value the description of experimental activities. This seems to be particularly relevant for first time entrepreneurs, suggesting that experimentation might be a substitute for experience. In my second essay, I examine the benefits of systematic and scientific experimentation vis-à-vis trial and error approaches commonly used by entrepreneurs. By embedding a field experiment in a pre-acceleration program, I follow a population of 251 entrepreneurs for a year. These entrepreneurs enter the pre-acceleration program with a vague business idea and are taught to use either a scientific approach to decision making (treatment) or a heuristics approach (control) in gathering and assessing information about the viability of their business ideas. Results show that treated entrepreneurs abandon seemingly unprofitable ideas earlier than entrepreneurs in the control group and that they pivot to ideas with better market potential. Finally, in my third essay, I explore factors that aid or hinder experimentation in the earliest possible stage of new venture creation: generation and selection of potential business ideas. This proposal illustrates the details of a field experiment embedded within a hackathon that will be conducted in 2019. Taken together, these essays contribute to enhance our understanding of how and when early-stage entrepreneurs can benefit from experimentation.

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1.

Introduction

It was already clear 100 years ago that problems can be solved quickly, cheaply and efficiently through experiments. Yet, it took a long time for this concept to make its way in the management and entrepreneurship literature. In recent years, however, experimentation has come to the forefront of the research agenda of scholars in strategy and entrepreneurship, and it is more clearly emerging as a way to gradually solve uncertainty and produce validated learning. While theoretical work is more clearly outlining that entrepreneurship – especially in the early-stages – is essentially about experimentation, we are yet to understand its impact and consequences on entrepreneurs.

This dissertation aims to address this gap by exploring the different ways in which experimentation impacts key milestones in the early stages of new venture creation. The three essays of my dissertation are based on the simple idea that systematic set of activities can be beneficial in the messy process of new venture creation. Experimentation (especially when systematic), by lowering the cost of learning, favours positive performance outcomes. Benefits of experimentation include signalling reliability to a crowd of resource providers, contributing to a better understanding of what will be required for a business to be successful, and potentially generating more promising business ideas. Chapter 2, in particular, highlights how experimentation can be beneficial for first time project creators on a funding platform. The finding that describing experimental activities to resource providers is less beneficial for experienced project creators, suggests that experimentation and experience might be substitutes. This results has been confirmed by some online experiments that replicate findings from the observational data and shed light on the key mechanisms behind this relationship. In chapter 3, instead, I focus on the role of a scientific approach to experimentation in the process of idea validation. The opportunity to closely follow a population of 251 early-stage entrepreneurs has generated insights into the activities entrepreneurs conduct in the early-stages of new venture creation. In chapter 4, I focus on what could aid experimentation in the process of identification of new business ideas. This dissertation contributes to the academic conversation on early-stage entrepreneurship and identifies a set of practices that can help entrepreneurs navigate the difficult process of new venture creation.

2.

Is Experimentation a Substitute for Experience? The Effect of Describing Planning and Experimentation on a Funding Platform

(Joint with Charles Williams)

Abstract

In early-stage entrepreneurship, we argue that descriptions of planning and *especially* experimentation activities will be valued by resource providers as a signal of the quality and the feasibility of new ventures. We evaluate 54,337 project descriptions posted by entrepreneurs seeking funds on Kickstarter to provide evidence of the impact of planning and experimentation activities on resource providers. Our results show that resource providers value the description of both planning and experimentation, with experimentation increasing the likelihood of funding especially for inexperienced entrepreneurs. The effect of describing experimental activities fades as entrepreneurs become more experienced, however, as experimentation and experience both signal learning by doing to resource providers. These patterns are replicated in online experiments, suggesting that they represent true causal relationships in the observational data.

Managerial abstract

As entrepreneurs start new ventures, they rely on resources they do not own or fully control. In communicating with resource providers, entrepreneurs make specific choices about what they disclose, and this can have a large impact on their likelihood of obtaining the resources they need. We study the description of experimentation- and planning-related activities – prominent aspects of the process of new venture creation – to show that they help elicit support from resource providers. By analyzing 54,337 project descriptions from Kickstarter, we find that describing experimentation- and planning-related activities results in an increase in the likelihood of obtaining funding. With the growing emphasis among entrepreneurs on experimentation and lean start-up techniques, this research clarifies if sharing these activities helps nascent entrepreneurs gain access to resources.

Keywords: entrepreneurship; experimentation; planning; entrepreneurial funding; crowdfunding; text analysis

2.1. Introduction

On what basis do resource providers decide to support new ventures? Like entrepreneurs, resource providers (investors and others) face significant uncertainty about the market potential of new products and services. Adding to this uncertainty, resource providers possess limited information about an entrepreneur's competency, reliability, and ability to execute on venture goals. This paper asks whether this uncertainty might be alleviated when entrepreneurs share details of their own approach to uncertainty, in particular concrete actions for planning or experimentation.

Planning and experimentation are two fundamental systems for addressing the uncertainty at the heart of early stage entrepreneurship. Planning manages, and in some ways minimizes, the uncertainty inherent in entrepreneurship by identifying key milestones and committing to timetables for their accomplishment. Experimentation, on the other hand, focuses on key uncertainties and targets them for exploration and learning through methodical trials and accelerated experience. While these activities are useful for the important task of refining an offering to meet the needs of a target market, we do not know when and how early-stage entrepreneurs might benefit from sharing how they have used them with potential resource providers who must be mobilized to create a final product.

Ample anecdotal evidence suggests early-stage resource providers value the description of concrete activities entrepreneurs conduct to establish a new venture. For instance, Brian Chesky and Joe Gebbia, who founded Airbnb in 2007, received investment based on the extreme measures they took to self-fund their venture; struggling to obtain seed funding, they had raised $30,000 by creating and selling limited edition election-themed cereal boxes during the US presidential election period. Paul Graham decided to invest because he was impressed by the pair's creativity: he took Chesky and

Gebbia's fundraising activities as a signal of their resilience in the face of the high uncertainty that surrounds the creation of new ventures. This and similar episodes raise the broader question of whether resource providers value the sharing of activities from the entrepreneurial process as a signal of the quality of the entrepreneur.

Answering the question of whether entrepreneurs can win over early-stage resource providers by sharing descriptions of their planning or experimentation activities can address two important areas of concern in the entrepreneurship literature. First, there is a lack of conclusive findings on whether sharing planning-related activities with investors increases the likelihood of obtaining funding. Research in this area (Delmar and Shane, 2003; Shane and Delmar, 2004; Dimov, 2010; Kirsch et al. 2009) has explored whether venture capitalists and other resource providers value business planning language in presentations of entrepreneurial projects, but findings remain mixed. Second, the growing emphasis on experimentation as an appropriate choice to improve performance in early-stage entrepreneurship (Murray and Tripsas, 2004; Kerr et al., 2014; Manso, 2016; Gans et al., 2018) does not shed light on whether describing experimentation helps attract resources or puts them at risk. Resource providers, in fact, might have to change the way that they evaluate ventures that are highly experimental, since these ventures tend to de-emphasize traditional metrics associated with planning, such as cost projections and detailed business plans, among others.

To understand these issues, our study theorizes that activities central to the process of new venture creation – such as planning and experimentation – are likely to provide cues that will be valued by a crowd of potential resource providers. Resource providers typically base their decisions on reports provided by entrepreneurs in pitches, business plans, and other documents. Because of the limited information available in these early-stage projects, we argue that resource providers value descriptions of planning- and experimentation-based activities as a signal of the quality and the feasibility of the project and the entrepreneur. In particular, experimentation activities can be useful for resolving uncertainty in the early stages of entrepreneurship and they showcase the challenging cognitive skills required to frame and conduct experiments. As a result, we expect they will be the most highly rewarded by resource providers.

We test our predictions using 54,337 project descriptions from Kickstarter, the largest crowdfunding platform for creative projects. This setting is ideal because it makes interactions and communications between founders looking for investments and potential resource providers observable and measurable. Unlike with venture capital and angel investors, where funding happens after a series of meetings behind closed doors, interactions between the entrepreneur seeking funds and resource providers are visible on Kickstarter.

Consistent with our predictions, we find that entrepreneurs describing activities related to planning or experimentation are more likely to obtain funding than entrepreneurs who do not. In particular, we find that describing experimental activities increases the likelihood of funding more than describing planning-related activities. This effect is even stronger for entrepreneurs without prior experience on the platform. In fact, there is no positive effect for experimentation when entrepreneurs return after two or more earlier projects on the platform. Planning, however, retains its value even for more experienced entrepreneurs. To check whether these findings represent true causal relationships, we conducted two online experiments that replicate the setting on Kickstarter with an audience of potential resource providers. Results from these experiments align with findings from the observational data from Kickstarter and show that the main driver of funding preferences for projects describing experimental activities is the perception of project creators as knowledgeable.

By exploring these issues in the context of early-stage entrepreneurial funding, we make contributions to research on entrepreneurship, entrepreneurial strategy, and entrepreneurial finance. A core premise of the entrepreneurship literature is that early-stage entrepreneurial ventures must orchestrate resources that they do not fully control; winning the backing of a variety of resource providers is essential to success. We show that entrepreneurs can win over potential resource providers by sharing experimentation and planning activities from their entrepreneurial process. We also contribute to the entrepreneurial strategy literature by showing that this positive effect interacts with the knowledge and experience of the entrepreneur in different ways for experimentation and planning. Experimentation appears to be a valuable substitute for knowledge from experience but – at least from the perspective of resource providers – prior experience also substitutes for the value of experimentation. In contrast, planning activities have value independent of the knowledge and experience of the entrepreneur. Finally, we contribute to the entrepreneurial finance literature by showing that early-stage resource providers value the language of experimentation in addition to planning.

2.2. Theoretical background

This paper builds from the research literature on entrepreneurial uncertainty and entrepreneurial signaling. Much of the existing literature has focused on various signals of the quality of the venture as determinants of the probability that an entrepreneur will obtain funding (Zott and Huy, 2007; Kirsch et al., 2009; Hsu and Ziedonis, 2013; Courtney et al., 2017). These studies largely examined communications with professional investors, such as venture capitalists, while, in this study, we focus on financial backers on a crowdfunding platform. We touch on potential differences between these funders – and why crowdfunders may be representative of an important, broader class of resource providers for early-stage entrepreneurs – when we address the study's limitations in the Discussion and Conclusion.

Prior studies build – in different ways – on signalling theory, which posits that observable signals can be informative and promote exchange between two parties in the presence of uncertainty and information asymmetry (Spence, 1973). From an economic point of view, signals need to indicate an important characteristic and be costly to send in a way that advantages more attractive ventures. In the context of entrepreneurial funding, studies that follow the economic tradition of signalling theory show that patents (Baum and Silverman, 2004; Hsu and Ziedonis, 2013), human and organizational capital (Baum and Silverman, 2004; Hsu, 2007), and high-status prior company affiliations (Burton et al, 2002) are costly and effective signals with resource providers.

Some studies, however, rooted in organization and sociology, have adopted a different perspective to signalling in the context of entrepreneurial funding. Lounsbury and Glynn (2001) started a tradition of studies that focus on the entrepreneurial stories that emphasize a firm's credibility to potential stakeholders, including investors. Scholars that follow this tradition of 'costless signals' focus on communication efforts that resonate with a key audience to help entrepreneurs gain access to resources. In this approach signalling refers to the communication of information that, while not costly, is nevertheless valued by audiences.

Zott and Huy (2007), for instance, focus on a variety of symbolic actions that represent signals of legitimacy and help entrepreneurs obtain resources. Kirsch *et al.* (2009) study planning references in documents submitted to venture capital (VCs) as signals that are weakly valued by resource providers. Likewise, Courtney *et al.* (2017) have used the information signal perspective in the context of crowdfunding to analyze how endorsements on social media and previous fundraising experience constitute signals that resource providers value. Given these findings, it seems natural that resource providers might also value descriptions of the entrepreneurial activities as signals about the entrepreneur and the project.

2.2.1. Planning and experimentation as entrepreneurial activities

Prior literature on entrepreneurship consistently describes two fundamental systems of activities that entrepreneurs can use to address the uncertainty at the heart of the entrepreneurial process: planning and experimentation (Wiltbank et al, 2006). The first, planning, emphasizes control over the future by delineating a set of concrete steps to reach an uncertain goal in the future, while the second, experimentation, emphasizes the identification and resolution of key uncertainties to foster learning about the appropriate and feasible goal.

Early-stage planning has been defined by Sexton and Bowman-Upton (1991, p.118), as the "process by which the entrepreneur, in exploiting an opportunity, creates a vision of the future and develops the necessary objectives, resources, and procedures to achieve that vision". Empirical evidence on the effect of planning on new firm performance is, however, limited and conflicting. Delmar and Shane (2003) find that business planning is beneficial to new firm survival. Brinckmann *et al.* (2010), through their meta-analysis of research on entrepreneurship, find that planning is beneficial for the performance of small and new firms. Greene and Hopp (2017) analyze ventures in the Panel Study of Entrepreneurial Dynamics and also find that planning is beneficial for performance. On the other hand, Bhidé (2000), Lange *et al.* (2007), and Dencker *et al.* (2009) find no effect. Notwithstanding the mixed findings, theory suggests that resource providers find shared planning activities reassuring because they identify goals and fill in concrete steps to reach them, reducing uncertainty.

At the same time, approaches that promote flexibility and faster learning in entrepreneurship have been championed by practitioners and scholars alike in the last 15 years. Entrepreneurial experimentation, broadly defined as a series of trial and error changes pursued along various dimensions of strategy over short periods of time, represents an effort to process information inputs from the environment and make rapid adjustments to a new venture. The idea that experimentation is better suited to complex and unstable environments has been popularized by movements such as design thinking (Dunne and Martin, 2006) and Lean Startup (Eisenmann et al., 2011). In parallel, emerging theories in entrepreneurship research such as effectuation (Sarasvathy, 2001) and entrepreneurial bricolage (Baker & Nelson, 2005) have developed explanations of entrepreneurial behavior that support the concept of experimentation. In line with these views, scholars have more recently identified experimentation as the most appropriate method to navigate the process of new venture creation (Kerr et al., 2014; Gans et al., 2018). In the face of irreducible uncertainty, which characterizes much of entrepreneurship, this work suggests that it is impossible to know *ex ante* which ideas are worth pursuing without taking action to explore their value in practice. With regard to recruiting resource providers, however, there are reasons to suspect that experimental approaches might deter audiences by highlighting uncertainty in the venture.

2.2.2. Does sharing entrepreneurial activities with resource providers help elicit resources?

Compared to entrepreneurs, resource providers have even less information about the new venture since they must depend on information shared by entrepreneurs (Brinckmann and Kim, 2015). Because of this information asymmetry, resource providers face considerable risks and potential adverse selection with regard to their funding choices (Michaely et al., 1994). When deciding whether to support a project, resource providers are simultaneously trying to evaluate the quality of the project and the capability of entrepreneurs to create the vision they lay out. Prior research has focused on how the quality of a project (Mollick, 2014) or the entrepreneurs behind it (Burns et al., 2016) will affect success. For this combined assessment of project and entrepreneur, we propose that the description of planning and experimental activities can increase the audience's perception that the project is feasible and strengthen the confidence that the entrepreneur has the capability to actually deliver on his/her venture.

Entrepreneurial activities presented in communications to resource providers, such as business plans, have been shown to legitimize new ventures and convince resource providers (Burton et al., 2002; Parhankangas and Ehrlich, 2014). Moreover, communications about activities carried out to establish a new venture play an even more important role in portraying a future reality when no product or service yet exists (Stone et al., 1996). Hence, communications regarding activities conducted to establish a new venture can help resource providers understand the new venture's potential and convince them of the capability of the entrepreneur to carry it to successful fruition.

In particular, descriptions of planning and experimentation activities reassure resource providers since they show entrepreneurs taking appropriate steps to address the uncertainty inherent in any opportunity. In the case of planning, resource providers are likely to be reassured by the definition of concrete steps to carry out the project, which reduces the apparent uncertainty of a venture. On the other hand, when entrepreneurs describe activities related to experimentation, they are sharing a learning process to explore uncertainty. In contrast to planning activities, experimentation tends to acknowledge more directly the uncertainty and exploit the opportunities for learning that it offers. Thus, in the face of uncertainty, experimentation activities can help entrepreneurs achieve a more complete understanding of what will be required for their venture to be successful (Murray and Tripsas, 2004). Both planning and experimentation activities require higher order cognitive skills to frame and conduct, so we expect they will be highly valued by resource providers. In sum, when entrepreneurs share planning- and experimentation-related activities, they provide further reassurance of their capabilities. Conversely, when entrepreneurs communicate with resource providers without showing a systematic approach to the process of new venture creation, they do not offer cues that reassure resource providers of the feasibility of their venture or their skills as entrepreneurs. For these reasons, we predict:

> **H1:** *Entrepreneurs who describe planning or experimentation activities are more likely to succeed in obtaining funds from resource providers.*

We also expect descriptions of planning- and experimentation-related activities to impact funding decisions differently. While both approaches address key risks and uncertainties associated with new ventures, experimentation offers more flexibility by aiming to learn directly from uncertainty. A key benefit of experimental activities over planning is that experimentation may be the most effective way to gather information and ultimately thrive in a dynamic and uncertain environment (Kerr et al., 2014; Camuffo et al., 2018). Experimental activities can, in fact, provide information about product feasibility (Murray and Tripsas, 2004), increase the entrepreneur’s knowledge of relationships amongst important business factors (Kerr et al., 2014), and ultimately provide further reassurance of the feasibility of a project (Camuffo et al., 2018). Planning activities, on the other hand, promise no learning or exploration. Instead, the planning approach tends to minimize uncertainty by segmenting it into specific steps and committing to overcoming it according to a specific timetable.

Since uncertainty cannot be completely eliminated as a factor in the entrepreneurial process (Knight,1921; Alvarez and Barney, 2007; Foss and Klein, 2012; Gans et al., 2018), activities that acknowledge it and exploit opportunities to learn have the potential to increase success more than activities that only minimize it. For resource providers, observing entrepreneurs using experimental methods to learn can provide an additional layer of reassurance that their expected returns will materialize: the activities signal the quality of the entrepreneur's process as well as the likelihood of success of the specific project. Accordingly, we propose:

> **H2:** *Entrepreneurs who describe experimental activities related to new venture creation are more likely than others to obtain funds from resource providers.*

2.2.3. When does sharing experimental activities with resource providers help elicit resources?

The knowledge that entrepreneurs possess is a key determinant of the nature of the opportunities that they pursue and their likelihood of success (Agarwal et al., 2007; Klepper and Sleeper, 2005). We posit that entrepreneurs' knowledge is also likely to shape their relationship with planning and experimentation and how audiences react to these shared activities. Prior research has focused on how funders react to individual characteristics such as gender (Marom et al., 2016) and credentials (Kang et al., 2016), but we focus on the role of prior *experience* in new venture creation. We argue that experienced entrepreneurs will benefit less than other entrepreneurs from sharing experimental activities, since both represent signals about the entrepreneur's knowledge developed through learning by doing.

A longstanding debate in entrepreneurial finance is whether to "bet on the jockey vs. bet on the horse" (Kaplan et al., 2009), but both sides recognize that funders are looking for reassurances of quality in both the project (the horse) and the jockey (the entrepreneur). Prior research has shown through interviews (Gruber et al., 2013) and surveys (Hsu, 2000) that entrepreneurs' experience is considerably valued by venture capitalists. Hsu (2000) in particular suggests that the positive correlation between prior experience and funding from VCs is compatible with a signaling effect to external resource providers. In the context of early-stage ventures, we expect experience with previous projects to signal that entrepreneurs have learned from prior experience in a specific domain. Since the description of experimental activities also signals a process of learning by doing, we expect the description of experimental activities to substitute or compensate for lack of experience in new entrepreneurs. In other words, entrepreneurs will benefit the most from describing experimentation (thereby showing learning by doing) when they lack prior experience. As entrepreneurs bring more prior experience, the signaling effect of learning through experimentation will become redundant and the value of the latter will fade.

> **H3:** *Describing experimentation activities will have more positive impact on funding for entrepreneurs with no prior experience than for those with more prior experience.*

2.3. Empirical setting

To examine the relationship between activities described by entrepreneurs and resources elicited we use data collected from the largest crowdfunding platform for creative projects: Kickstarter. Within Kickstarter, entrepreneurs create projects that can be supported by individuals (called backers) who obtain a reward in return for small amounts of money. If projects achieve their funding targets by a designated deadline, they receive the full amount pledged by backers. If not, the project creators do not receive any funding.

While crowdfunding is a relatively new phenomenon, it is considered an established source of early-stage financing for entrepreneurs (Wright et al., 2016). During crowdfunding campaigns, entrepreneurs interact with an audience that differs from traditional investors such as venture capitalists or angel investors. Backers are a mix of domain experts, enthusiasts, and laypeople who primarily support projects because of their interest in a product rather than as financial investments. Kickstarter is an ideal setting to study the effect of describing planning- and experimentation-related activities on funding because it provides a large population of early-stage entrepreneurs presenting new venture ideas to an audience of potential resource providers. These entrepreneurs have normally taken some steps to develop their idea, but they rarely present a fully functional product. Given the stage of development of their venture, they often describe the activities conducted to create a new product in order to mobilize support. Moreover. using this setting allows us to overcome empirical challenges traditionally associated with studying early-stage financing, a phenomenon that is difficult to observe and measure. Finally, in this setting we observe entrepreneurs operating in multiple domains (thus avoiding idiosyncrasies related to one specific industry), and we observe both projects that reach their funding goals and projects that do not (avoiding survival bias). Through web-scraping software, we collected detailed information regarding all projects launched on Kickstarter from the beginning of March 2016 to the end of February 2017. Our dataset comprises 54,337 projects across 14 different product categories.

2.3.1. Measures

Dependent variable(s)

The dependent variable in our model is the crowdfunding project's success in attracting resources, which we operationalized using a binary variable (Success) that indicates whether or not entrepreneurs reached their funding goal by the stated deadline. In robustness analysis we also examined continuous variables such as the amount of money raised and the number of resource providers that entrepreneurs attract.

Explanatory variables

Planning/Experimentation activities: We used natural language algorithms to create measures to capture the entrepreneurial activities that founders describe in relation to their project. On the platform, entrepreneurs provide a project description that ranges from 99 to 32759 words. We followed the procedure proposed by Short *et al.* (2010) to ensure the validity of the content coded using computer aided text classification. Results from structured keyword searches build on research in psychology (Pennebaker et al., 2003) in order to capture underlying constructs through natural language (McKenny et al., 2016). We explain the coding process in detail in the Online Appendix and summarize it in Figure 1 below:

Figure 1. Description of the coding process utilized, adapted from Short et al. (2010)

Step 1	Identification of a formal definition of planning and experimentation from literature on early-stage entrepreneurship
Step 2	Assessment of key components of planning/experimentation based on review of the literature (key components of the construct)
Step 3	Development of an exhaustive list of words that identify key constructs of interest
Step 4	Validation of these lists with external raters (calculating inter-rater agreement)
Step 5	Performing initial keyword search using the list validated by the raters
Step 6	Refinement of the word list through manual screening of results of keyword search
Step 7	Modifying the search algorithm to reduce false positives/false negatives

Our process relies on a keyword search using terms derived from a literature review on the topic of planning and experimentation in early-stage entrepreneurship. External raters validated the lists of words derived from this literature,[1] and these lists were the basis for searches of the project descriptions using functions in Python's NLTK library. We generated three binary variables (one for planning, one for experimentation, one for both planning and experimentation) equal to 1 if a keyword is present in a sentence of a project description and equal to 0 otherwise. For each project description, we also report a count of the sentences containing keywords related to planning, experimentation, or both.

Since keyword searches come with a certain degree of measurement error, we performed additional steps to quantify and reduce the occurrence of false positives and false negatives in the search results. For instance, we found regular occurrences of "Kickstarter goal" which refers to the amount of money targeted by the entrepreneur and not a goal for planning activities. We catalogued all such pairs of words, or bigrams, and removed them from the text. The Online Appendix provides a list of keyword inclusions and exclusions.

Control variables

- *Staff Pick:* a dummy variable that indicates when projects are featured on Kickstarter's home page and in its newsletter to control for the increased visibility.
- *Goal Amount:* the logarithm of total funding requested for the project. Prior studies suggest that this target provides a signal regarding the quality of the project (Colombo et al., 2015) and thus the goal amount affects funding decisions.

[1] The list of keywords for planning and experimentation is available in the Online Appendix.

- *Duration of campaign:* the pre-determined duration of the crowdfunding campaign. Kickstarter allows project creators to choose how long their campaign will last, and longer campaigns may benefit from increased visibility on the platform.
- *Length of project description:* the length of the project description as a count of sentences. The quantity of information provided in the project description could affect its signal value (Mollick, 2014).
- *Number of projects backed by the project creator:* a count prior to project launch. According to Zvilicovski *et al.* (2015) entrepreneurs that back other projects on Kickstarter are more likely to obtain resources from other entrepreneurs on the platform.
- *Number of projects created by the project creator:* the number of projects that entrepreneurs created on Kickstarter prior to launching the current project. Entrepreneurs who have previously created projects might benefit from prior experience on the platform, for instance by recruiting donations from previous backers.
- *Number of Facebook friends*: the number of Facebook friends of entrepreneurs launching projects on Kickstarter. Prior studies have shown that friends and family are much more likely to contribute to projects (Marom et al., 2016).
- *Number of comments on campaign:* the number of comments on each Kickstarter campaign. Comments are posted both by entrepreneurs and potential resource providers, and we use them as a proxy for the total engagement with the project.
- *Credentials:* a dummy variable equal to 1 if project creators mention any credentials in their profile or project description and equal to 0 if they do not. Credentials include: (i) mentions of prizes and awards, (ii) education-related

credentials (mentioning a degree), and (iii) professional credentials (if project creators describe themselves as founders or CEOs). We code credentials using the NLTK library in Python and a keyword approach. We use credentials as a proxy for the quality of the project and entrepreneur.

- *Product novelty*: a dummy variable equal to 1 if the project description contains words associated with novelty, and equal to 0 if it does not. We derived words associated with novelty through projects classified as innovative by Kickstarter.
- *Tone*: the extent to which the project includes positive vs negative words, following recommendations from Anglin *et al*. (2018) and using the Linguistic Inquiry Word Count (LIWC) software.
- *Number of rewards offered:* the number of rewards each project offers, as this might result in a higher number of backers contributing to a particular project.
- *Category:* a dummy for the domain category in which each project is listed.
- *Start date:* the month in which each project is launched on Kickstarter, since funding dynamics change in relation to the time of the year (Burtch et al., 2018).

2.3.2. Descriptive statistics

Our final dataset comprises 54,377 projects that were launched and concluded on Kickstarter between March 2016 and February 2017. We exclude project descriptions in languages other than English. Some projects raised funds in currencies other than USD, so we converted all amounts to USD using the official exchange rate provided by the European Central Bank as of April 1st, 2017. As shown in Table 1, on average each project attracted $11,807 in pledges from 128 backers. Thirty-four percent of projects were successful in achieving their funding goal. Approximately 56 percent of the projects in our sample describe planning-related activities, while 19 percent describe experimentation-related activities, and 12 percent describe a mix of planning and experimental activities.

Table 1. Descriptive statistics for main variables

Variable	Mean	SD	Min	Max
Goal (USD)	56,172.95	1,320,302	.5	106,732,471
Amount Raised (USD)	11,807.44	11,4674.4	0	12,779,843
Resources (% of goal)	7.35	578.89	0	104,277
Backers (number)	128.24	1048.13	0	154,926
Backed by creator	5.59	24.87	0	1,903
Number of Facebook friends	463.64	859.59	0	4,999
Number of comments	15.19	68.63	0	997
Length of project description (sentences)	30.91	28.85	1	423
Created by creator	1.66	2.48	1	78
Duration of campaign (days)	31.79	12.92	0	64
Success	0.34	0.47	0	1
Experimentation	0.19	0.39	0	1
Planning	0.56	0.49	0	1
Both	0.12	0.33	0	1
Neither	0.37	0.48	0	1
Credentials	0.07	0.25	0	1
N	54337			

2.3.3. Statistical methods

We examined relationships between activities described by entrepreneurs and funding success using logistic regressions, since the dependent variable in this equation is a binary measure of whether entrepreneurs achieve their funding goal by the deadline (success). We estimated the following equation:

$$P(Y=1|X)=Y^{\wedge} = \beta_0 + \beta_1 X_1+\beta_2 X_2 + \beta_3 X_3 + \beta_4 F + \varepsilon \qquad (1)$$

In equation (1) the variable Y (success of funding campaign) is defined as a linear probability function of the activities described by entrepreneurs (X). We included experimentation (X_1), planning (X_2), and a combination of the two (X_3), and used the lack of planning or experimentation in the project description as the omitted state which provided a baseline for the interpretation of the results of the regression. The control variables are denoted by the vector F, and the residual random variation is represented by the term ε. Since we used logistic regressions, we also present estimates of the marginal probability of success, which varies based on the level of the independent variables.

Despite the inclusion of many controls, this analysis cannot definitively establish a causal relationship between the description of experimentation- or planning-related activities and success. In fact, we were not able to completely rule out self-selection of entrepreneurs in approaches to new venture creation, as more capable entrepreneurs might conduct experimental activities. There might also be omitted variables that affected both our dependent and independent variables, creating potential confounding effects in our analysis. Our setting does not present opportunities for identification strategies that rely on instrumental variables or natural experiments. For this reason, we also conducted two online experiments that replicated the Kickstarter setting and which are described in detail in their presentation as study one and study two.

2.4. Results

In reporting the results of our statistical analysis, we report standard errors and discuss exact p-values without referring to conventional cut-off levels of statistical significance. This choice is consistent with the increasing emphasis on the need to develop more appropriate norms around the use and interpretation of statistics by Bettis *et al*. (2016). Table 2 shows our estimates with success as the dependent variable. Column (1) presents the basic model and (2) includes controls for start date and project category. Column (3) includes project-level controls and (4) adds creator-level controls. As we add controls, the sample drops slightly, as shown in Table 2. The results in the first column of Table 1 suggest that describing planning and experimentation increases the likelihood of successful funding. In particular, describing planning or experimental activities is associated with a positive chance of funding success, compared to the baseline. The coefficient for planning is higher than the one for experimentation, and both variables have small p-values. The Both variable (when Planning and Experimentation are both mentioned) has a negative coefficient, thus indicating that the effects of Planning and Experimentation are not fully additive. Results reported in columns 2, 3, and 4 show that the description of planning- or experimentation-related activities in project descriptions is sensitive to the inclusion of controls that represent the type and the nature of the project and the project creator. In the final model, the estimates show that experimentation activities have a positive impact on successful funding (coefficient: 0.34, p-value=0.000), and the coefficient for planning decreases to 0.24 (p-value=0.000), thus indicating that both activities significantly increase the likelihood of obtaining funds compared to projects that do not describe any of these activities. We also computed marginal effects to assess the economic significance of describing these activities on the likelihood of obtaining funding. Results show that compared to the baseline (no description of planning-related or experimental activities), Experimentation increases the likelihood of obtaining funds by nearly seven percent, while Planning increases this likelihood by nearly five percent. We also performed a Wald test of the likelihood that experimentation was larger than planning, and the two coefficients were meaningfully different from each other (p-value=0.003). These results, then, are consistent with hypothesis 1 and hypothesis 2.

Table 2. Effect of Planning, Experimentation and Hybrid on performance, DV: Success, logistic regression reporting coefficients.

VARIABLES	(1) Success	(2) Success	(3) Success	(4) Success
Experimentation	0.189	0.385	0.514	0.345
	(0.0393)	(0.0411)	(0.0441)	(0.0484)
Planning	0.357	0.359	0.406	0.242
	(0.0205)	(0.0211)	(0.0228)	(0.0251)
Both	-0.0676	-0.0926	-0.0998	-0.0959
	(0.0482)	(0.0495)	(0.0531)	(0.0582)
Staff pick			2.680	2.225

			(0.0534)	(0.0567)
Length description			0.00216	0.00134
			(0.000348)	(0.000386)
Length funding period			-0.00886	-0.00562
			(0.000872)	(0.000965)
Goal			-0.361	-0.502
			(0.00675)	(0.00812)
Rewards			0.128	0.129
			(0.00217)	(0.00243)
Product novelty			-0.00716	-0.00532
			(0.0235)	(0.0257)
Tone			0.00757	0.00515
			(0.000442)	(0.000486)
Created by creator				0.0557
				(0.00609)
Backed by creator				0.157
				(0.00329)
Number of FB friends				0.000111
				(1.28e-05)
Control for category	No	Yes	Yes	Yes
Control for start date	No	Yes	Yes	Yes
Constant	-0.895	-0.728	1.750	1.621
	(0.0155)	(0.0436)	(0.0781)	(0.0878)
Observations	54,337	54,278	54,260	54,260

Standard errors in parentheses

In order to test hypothesis 3, we ran the same regressions used in Table 2 but for our subset of interest: experienced project creators. We ran regressions on sub-samples to more clearly show the effects of Experimentation and Planning at different levels of experience and report them in Table 3. Interestingly, coefficients for first-time and second-time project creators were very similar. Once project creators had created three projects, the positive effect of experimentation on the likelihood of success disappeared. With regards to planning, however, we observed a positive and statistically meaningful effect until projects creators had created four campaigns, after which coefficients remained positive but p-values became rather large. After four projects, the coefficient for experimentation becomes negative. These results are in line with what we observed when we used experience as an interaction term – the interaction with experimentation became negative, while the one with planning remained positive. For brevity’s sake we do not report results using the interaction term, but they are available upon request.

Table 3. Effect of Planning and Experimentation on performance, DV: Success, logistic regression reporting coefficients

Sample	Sample size	Experimentation		Planning	
		B	p-value	β	p-value
Complete sample	54,337	0.34	0.000	0.24	0.000
Created=1	41,326	0.37	0.000	0.22	0.000
Created=2	7,260	0.38	0.002	0.22	0.001
Created=3	2,293	0.00	0.971	0.16	0.178
Created=4	1,032	0.35	0.276	0.78	0.000
Created=5	597	-0.03	0.936	0.16	0.502
Created=6	462	-0.82	0.145	0.33	0.252

2.5. Robustness checks

One concern might be that Kickstarter provides a sample that is not relevant for entrepreneurship more broadly, as many project creators on the platform are artists who require small amounts of money or obtain funding from family and friends. We addressed these issues by running the same regressions only for projects that set their funding goal at 10,000 USD or above – a threshold that should account for the dynamics described above. Despite reducing our sample to 23,238 projects, regressions reported in Table 4 show that our results are in line with results presented in Table 2. Coefficients from this analysis indicate a weaker effect for the description of planning- or experimentation-related activities, showing that the coefficient for planning remains positive and roughly of the same size (coefficient: 0.25, p-value=0.000) compared to projects that do not describe entrepreneurial activities, and experimentation retains a positive coefficient that becomes smaller (coefficient: 0.29, p-value=0.000).

Table 4. Effect of Planning, Experimentation and Hybrid on performance, DV: Success, logistic regression reporting coefficients, only for projects with a Goal above $10,000

VARIABLES	(1) Success	(2) Success	(3) Success	(4) Success
Experimentation	0.467	0.536	0.502	0.293
	(0.0624)	(0.0647)	(0.0702)	(0.0768)
Planning	0.550	0.541	0.464	0.250
	(0.0388)	(0.0394)	(0.0430)	(0.0477)
Both	-0.206	-0.191	-0.137	-0.0737
	(0.0745)	(0.0759)	(0.0828)	(0.0907)
Staff pick			2.789	2.310
			(0.0657)	(0.0701)
Length description			0.00351	0.00248
			(0.000579)	(0.000646)
Length funding period			-0.00492	-0.00275
			(0.00153)	(0.00173)
Goal			-0.614	-0.736
			(0.0241)	(0.0281)
Rewards			0.119	0.117
			(0.00325)	(0.00345)
Product novelty			0.0423	0.0550
			(0.0402)	(0.0442)
Tone			0.0105	0.00667
			(0.000834)	(0.000923)
Created by creator				0.0815
				(0.0124)
Backed by creator				0.157
				(0.00522)
Number of FB friends				9.78e-05
				(2.12e-05)
Controls for category	No	Yes	Yes	Yes
Controls for start date	No	Yes	Yes	Yes
Constant	-1.607	-1.601	3.716	3.646
	(0.0312)	(0.0864)	(0.266)	(0.304)
Observations	23,238	23,238	23,199	23,199

Standard errors in parentheses

We also conducted several robustness checks across different dependent variables and statistical specifications. We ran Poisson regressions using as dependent variables the log of the amount of money raised (in USD) and the number of backers attracted and we found the same results, where experimentation results in the largest and positive coefficient compared to planning, both, and baseline. For brevity's sake, we do not report these additional results, but they are available upon request.

2.6. Online experiments

Since causal identification is challenging with the Kickstarter data, we conducted two online studies to test if results from observational data can be replicated in an experimental setting. The first study aimed to replicate findings from the observational data to assess if participants report a higher willingness to fund crowdfunding projects when reading descriptions containing experimentation-/planning-related activities. The goal of the second study was to check if the reported willingness to fund projects is also influenced by the prior experience of project creators. Additionally, the second study provides insights into the mechanisms behind the positive perception of the description of experimentation-/planning-related activities.

The two experiments were conducted in October and December 2018 on Prolific, a platform that connects researchers with participants for human intelligence tasks or experiments. Prolific represents a suitable setting for our experiment, as online experiments have been shown to produce results analogous to those conducted in a laboratory (Berinsky et al., 2012). The experiments were designed to build on results from our dataset in three key ways. First, in both cases we used the same actual project from our sample that we slightly modified to make sure that participants could not identify the Kickstarter project used for the online experiment. Second, we replicated the language used by entrepreneurs on Kickstarter when describing planning- or experimentation-related activities. Finally, we used a representative sample of potential resource providers who might be active on crowdfunding platforms[2].

2.6.1. Study 1: Planning and experimentation in an online experiment

Prolific provides a pool of about 33,000 eligible participants. One of the main concerns with online experiments is that participants might carry out tasks without paying attention, providing random responses. To address this issue, we included an attention check at the beginning of the survey, following the indications provided by Berinsky *et al.* (2014). Participants who failed to select the correct answer for the attention check answer were excluded. Our final sample includes 500 participants randomly allocated across five conditions.

The set up was as follows. We informed participants that Crowd Innovation Lab (a fictitious company that invests in promising projects from crowdfunding platforms) was using Prolific to conduct market research to decide whether or not to invest in new products available on crowdfunding platforms. Participants were de-briefed at the end of the experiment and informed that the company was fictitious. We introduced this fictitious company because we wanted participants to believe that real resources were going to be invested in the project, thus seeking to increase the attention participants paid to this task. Participants who volunteered for the experiment and passed the attention check were then shown a modified project description from a real Kickstarter project from our sample (we removed identifying details). The product was a new type of pillow, which featured adjustable height, extra softness, and customizable options. We chose a pillow because it is a gender-neutral product that everyone uses on a daily basis and that

[2] The pool of participants on Prolific is considered similar to Amazon Mechanical Turk, with the minimum threshold for pay being higher.

is not normally associated with a strong emotional response. The experiment is reproduced in the Online Appendix. We randomly assigned 500 participants to one of five conditions, opting for a between-subject design. Participants received the same information about the pillow across all five conditions, while the treatment involved variation in the activities described by the entrepreneur, as described in Table 5. Participants were then asked to report the extent to which they would like to fund the project. Participants were only allowed to participate in this experiment once.

Table 5. Description of conditions and manipulations for study 1 on Prolific

Condition	Manipulation	Number of participants
1. Experimentation	The entrepreneur describes how he/she conducted experimental activities when creating the pillow	100
2. Planning	The entrepreneur describes how he/she carefully planned each step of the process when creating the pillow	100
3. Hybrid	The entrepreneur described how he/she conducted both experimental activities and planned each step of the process when creating the pillow	100
4. No description of activities (no words)	There is no description of activities in this condition	100
5. No description of activities (neutral words)	There is a description of activities in this condition, but without any reference to either planning or experimentation.	100

Allocating participants to five conditions allowed us to replicate the different scenarios potentially faced by backers on Kickstarter. In particular, we observed that on Kickstarter project creators either did not describe activities conducted to create their product or described activities without referring to either planning or experimentation. We included both neutral conditions in our experimental setting, but we show results with a single baseline condition with a neutral description of entrepreneurial activities (no planning or experimentation), which results in the most conservative findings. Results are almost identical when we use as a baseline the project that does not contain any description of the activities conducted by the entrepreneur. For brevity's sake we do not report these additional results, but they are available upon request.

2.6.2. Study 1: Results

With this study, we measured the fictitious crowdfunding project's success in attracting resources, which we operationalized using a binary variable that indicates whether or not participants reported willingness to fund the project they read about. Results presented in Figure 2 and Table 7 show that participants were more willing to fund projects that describe experimentation-/planning-related activities, but that there were no meaningful differences between projects that describe planning and experimentation. The project that contained a description of experimental activities in developing the pillow, in particular, resulted in a 17% (p-value= 0.013) increase in the reported likelihood to provide funding compared to conditions without a description of entrepreneurial activities, and this difference is statistically compelling given the low p-value. The condition *planning* resulted in a 12% (p-value=0.079) increase in the reported likelihood to provide funding compared to the condition where there is no description of activities. Overall, these results show that describing experimentation- or planning-related activities is valued by a crowd of potential backers, as indicated by participants reporting a higher willingness to fund the project. This result is consistent with the analysis from the observational data conducted on Kickstarter, since the direction of the effects in the experimental setting appears comparable. As shown in Table 6, the direction of the coefficients for experimentation, planning, and hybrid is consistent with the observational data, but the magnitude of the effects is larger in the experimental setting. This might be due to the fact that there was limited information available to resource providers in the experiment and this could have resulted in the increased weight the description of activities seems to carry. Results are consistent when we use a different dependent variable (such as amount of money that participants would donate to the project), and become stronger when we restrict the sample to participants with previous experience on crowdfunding platforms.

Figure 2. Reported willingness to fund Kickstarter project per experimental condition, study 1.

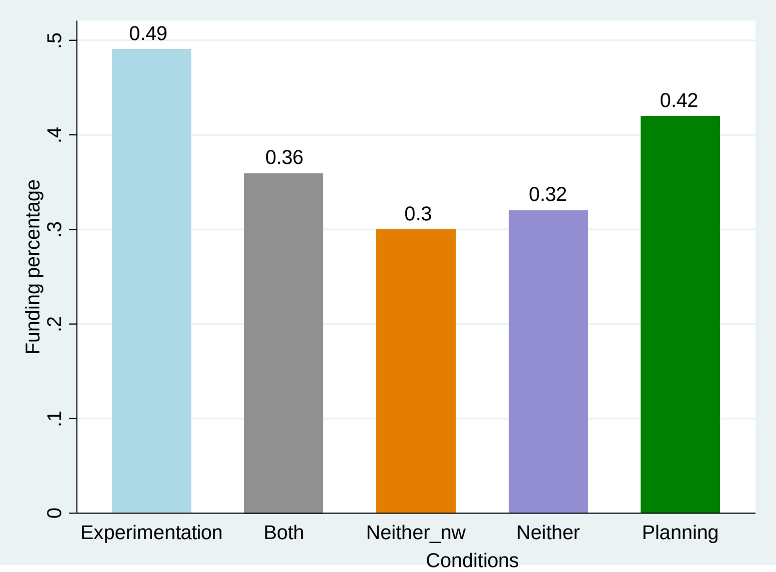

Table 6. Study 1: Effect of Planning, Experimentation and Hybrid on funding, DV: success, logistic regression reporting coefficients

VARIABLES	(1) Success
Experimentation	0.807
	(0.296)
Planning	0.525
	(0.298)
Hybrid	0.272
	(0.302)
Neither (no words)	0.0935
	(0.306)
Constant	-0.847

	(0.218)
Observations	500

seEform in parentheses

2.6.3. Study 2: Experience, planning, and experimentation in an online experiment

The goal of the second study was to build on the first experiment by focusing on interactions between the description of experimentation- or planning-related activities and experience while shedding light on key mechanisms behind participants' funding preferences. We used the same setting (Prolific) and the same protocol (a fictitious crowdfunding project to produce a new pillow) as in study one. The key difference was that in study two we measured how constructs related to the key uncertainty associated with crowdfunding projects vary with different descriptions of activities (planning, experimentation, control) and levels of experience of the project creator (first-time vs. experienced creator).

The study design is as follows. Participants were asked to correctly answer an attention-check question before being randomly assigned to different version of the same fictitious crowdfunding project (pillow) used in study one. For this reason, we restricted participation to users on Prolific who did not participate in study one. We randomly assigned 600 participants to one of six conditions, opting for a between-subject design. Participants were shown the same product description across all six conditions. The treatment involved variation in the planning or experimentation activities described by the entrepreneur, as well as their prior experience with crowdfunding projects (described in Table 7). We collected information regarding the reported willingness to fund the project. Participants were allowed to participate in this experiment only once.

In study two we introduced four questions that aimed to assess the extent to which judgement about the project or the founder changed alongside the type of activities described (planning, experimentation, control). We were interested in whether a description of the activities conducted resolved key uncertainties associated with new projects, so we measured market uncertainty, product uncertainty, project uncertainty, and founder uncertainty using Likert scales (1-5). We also collected measures of the reported willingness to fund the project. The experiment and our measures of uncertainty are reproduced in the Online Appendix.

Table 7. Description of conditions and manipulations for study two on Prolific

Condition	Manipulation	Number of participants
1. Experimentation – first-time project creator	The entrepreneur describes how he/she conducted experimental activities when creating the pillow and we highlight that this is his/her first project	101
2. Planning – first-time project creator	The entrepreneur describes how he/she carefully planned each step of the process when creating the pillow and we highlight that this is his/her first project	101
3. Control – first-time project creator	The entrepreneur describes generic activities when creating the pillow (without referring to either planning or experimentation) and we highlight that this is his/her first project	99
4. Experimentation – third-time project creator	The entrepreneur describes how he/she conducted both experimental activities and planned each step of the process when creating the pillow and we highlight that this is his/her third project	99
5. Planning – third-time project creator	There is no description of activities in this condition and we highlight that this is his/her third project	99
6. Control – third-time project creator	The entrepreneur describes generic activities when creating the pillow (without referring to either planning or experimentation) and we highlight that this is his/her third project	101

2.6.4. Study 2: Results

Results presented in Table 8 and Figure 3 show that participants were significantly more willing to fund projects that describe experimental activities when the project creator had no prior experience with crowdfunding projects. For a third-time project creator describing experimental activities, his/her chances of success decreased by 17% compared to a first-time project creator using the same description of experimental activities (p-value=0.006). With regards to planning, the effect of experience was positive, as participants assigned to the condition *planning third* reported a higher willingness to fund the project than participants assigned to the conditions *experiment third* (p-value=0.015) and *planning first* (p-value=0.367). Finally, participants assigned to the conditions *planning first* and *experiment first* showed a higher willingness to fund those projects than participants assigned to the condition *control first*. Taken together, these results show that the description of experimentation- or planning-related activities is valued differently by a crowd of potential backers depending on the experience project creators have on the platform. This is consistent with the analysis from the observational data conducted on Kickstarter, since the direction of the effects in the experimental setting appears comparable with results from Kickstarter.

With regards to the measures of uncertainty, we did not find large effects for measures of market uncertainty, product uncertainty, or project uncertainty. We did find, however, differences across conditions in terms of how knowledgeable the project creator is perceived to be. Consistently with results shown in Table 8, first-time project creators describing experimental activities were rated 19% more knowledgeable than first-time project creators not describing activities, and this difference had a reasonable p-value (0.091), thus suggesting a meaningful relationship. With regards to planning, the effect of experience is positive, as participants assigned to the condition *planning third* were perceived to be more knowledgeable than either first-time or third-time project creators who either described experimental activities or who did not describe any activities. Overall, it appears that experienced creators who describe experimental activities are not perceived as knowledgeable, unlike experienced creators who either describe planning-related activities or no activities at all.

Figure 3. Reported willingness to fund Kickstarter project per experimental condition, study 2.

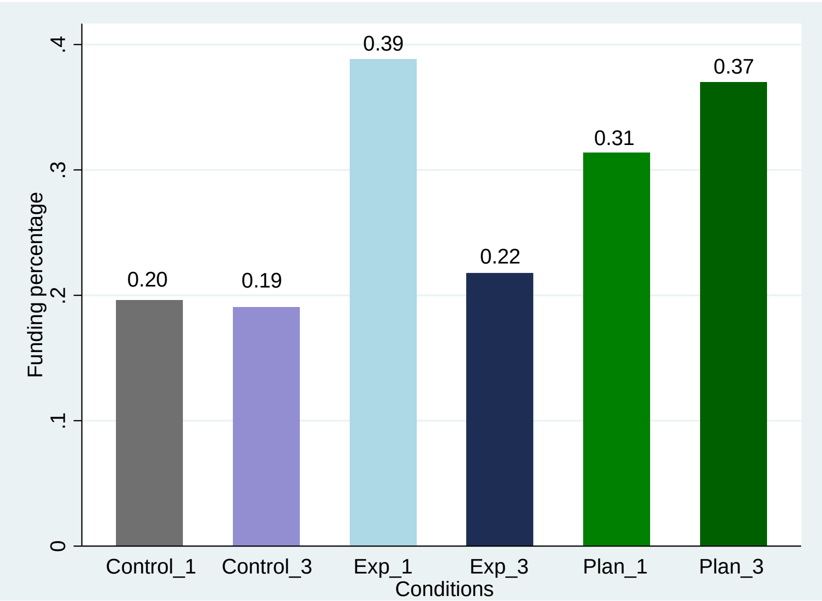

Table 8. Study 2: Effect of Planning, Experimentation on funding with interaction for experience, DV: Success, logistic regression reporting coefficients

VARIABLES	Success
Experiment first	0.957
	(0.321)
Experiment third	0.133
	(0.347)
Planning first	0.628
	(0.328)
Planning third	0.879
	(0.324)
Control third	-0.0359
	(0.352)
Constant	-1.411

	(0.249)
Observations	600

seEform in parentheses

Table 9. Study 2, Experiment two on Prolific. DV: Perceived knowledge of project creator, OLS regression

VARIABLES	Knowledge scale
Control first	0.00140
	(0.135)
Experiment first	0.231
	(0.135)
Experiment third	-0.0146
	(0.135)
Planning first	0.0798
	(0.135)
Planning third	0.399
	(0.136)
Constant	3.381
	(0.0947)
Observations	600

seEform in parentheses

2.6.5. Discussion of experimental results

These two experimental studies provide evidence that is consistent with results from observational data collected on Kickstarter. The comparison between these two sets of results shows that despite causality concerns, results from observational data appear robust and suggestive of a meaningful relation between the description of experimentation- and planning-related activities and success with a crowd of potential investors.

In both settings, the description of experimental activities is valued to a large extent by resource providers, but it does not seem to retain its value as project creators gain experience on the funding platform. The description of planning-related activities, however, is valued by resource providers and seems to retain its value longer than the description of experimental activities. Moreover, we found evidence that judgement about project creators changes most with experimentation and planning, especially with regards to how knowledgeable they are perceived to be. In particular, the description of planning-related activities by experienced creators is strongly associated with knowledge. Meanwhile, it appears that first-time project creators who describe experimental activities are perceived as more knowledgeable, thus supporting the idea that experimentation might compensate for a lack of experience and its associated knowledge.

2.7. Discussion and conclusion

Most scholars in entrepreneurship agree that the fundamental characteristic that distinguishes entrepreneurship from other business activities is the deep uncertainty at the heart of new venture creation. In this study, we describe planning and experimentation as two canonical systems by which entrepreneurs identify, learn from, manage, and minimize uncertainty. We found that entrepreneurs can attract resource providers when they share these activities since they help signal and affirm the quality and resilience of the venture founders. While both systems share the aim of addressing uncertainty, they do so in very different ways. Planning generally contains and minimizes uncertainty through specific goals, targets, and timetables, while experimentation develops opportunities for learning by doing focused on key uncertainties. These different approaches, it turns out, also interact with entrepreneurs' knowledge in different ways. Prior experience has been shown to have important effects on the outcomes of entrepreneurship (Klepper, 2001; Chatterji, 2008; Agarwal et al., 2004), and this study extends that work to show that it also affects the processes that entrepreneurs adopt and activities that they undertake to develop the venture.

For entrepreneurship scholars, our key finding is that resource providers react positively when early stage entrepreneurs share information related to planning and experimentation activities. These findings connect with studies that focus on understanding how early-stage entrepreneurs engage and enrol stakeholders under conditions of high uncertainty (Burns et al., 2015; Alvarez and Sachs, 2018). Research in this area has primarily involved conceptual work, but has struggled to empirically test theory given the challenges associated with studying early-stage entrepreneurship. Since early-stage entrepreneurs must mobilize many resources they do not fully own or control, understanding how these different audiences will react to shared process activities is important both from a theoretical and a practical standpoint.

One further contribution of this study is that we provide systematic evidence that planning and experimentation activities may interact with – and substitute for – knowledge and experience in different ways. Strategy, and the entrepreneurial strategy literature, have frequently focused on the central role of knowledge and prior experience for entrepreneurial success (Grant 1996; Gruber, 2007; Dencker et al., 2009). In this study, we find that resource providers especially value experimentation activities in first-time entrepreneurs, but not when they have more experience. This suggests that outside audiences see experimentation as substituting for the knowledge generated by experience, but not extending or amplifying it. Planning activities, on the other hand, do not undermine the assessment of entrepreneurs' knowledge: they are equally valued for new and more experienced entrepreneurs.

Our study also has important implications for the entrepreneurial finance literature. In this stream, studies have examined the value of planning activities to later-stage resource providers, such as venture capitalists and angel investors. This study extends the relationship to earlier-stage financing provided by crowdfunding platforms and finds less equivocal evidence that, at least in early stages, planning activities are valued by providers of financial resources. In addition, the reaction of important audiences to the sharing of experimentation activities has not previously been explored in the entrepreneurship or entrepreneurial finance literature. This study provides evidence that, for early-stage venture formation, not only is experimentation valued, it is rewarded at higher rates than planning.

The elements of this study, naturally, have limitations in the strength and generality of their conclusions. Some of the limitations are answered by other parts of the study. For instance, a natural limitation of the observational study of Kickstarter projects is that the regression analysis may identify relationships that are not truly causal. But the experimental studies confirm that key relationships do actually represent causal relationships. A common concern with experimental findings is whether they will generalize to the real world, so the fact that these relationships arise in a popular online funding platform eases this concern.

The natural language processing method used to analyse the Kickstarter data has limitations, as well. In many studies, there is a concern that the language of description might not represent the actual behaviour of study participants. This is less of a concern in this case, since the focus of the study is communication between project creators and potential resource providers. False positives and false negatives are also possible, in which the algorithm identifies passages as relating to experimentation or planning when a human coder would not (and vice versa). But as we detail in the Online Appendix, we added additional steps to the typical NLP method to identify and remedy false negatives and false positives.

Another common concern with studies of crowdfunding is that this activity is different from the professional investing that occurs later in the development of an entrepreneurial venture. It is possible that early-stage resource providers might value experimentation more than professional investors will in later stages since early venture development is generally more fluid than later stages. The fact that funders also value planning may suggest that this is less of a concern, but the value of experimentation for late-stage entrepreneurial finance remains an important question for future research. In addition, while backers in crowdfunding may not be a perfect analogue of professional investors, they are representative of a broad class of informal resource providers – those providing early labour, places to work, feedback on ideas, and customer engagement – who are vital for early-stage ventures. It is also a concern that projects on Kickstarter are not representative of entrepreneurship since they include a variety of arts-based initiatives in film, theatre, dance, and publishing. To account for this, in robustness analysis we limited our analysis to projects of $10,000 or more and to design and technology categories that are more business-driven, and we found the results were, if anything, starker than in the full sample.

Finally, our study focuses on resource providers for entrepreneurship but reveals an interesting question for entrepreneurial strategy: is experimentation less helpful for entrepreneurs with prior experience? The limitations on the value of experimentation might only be relevant to the relationship with resource providers who do not distinguish between the two forms of learning by doing. Alternatively, it could be that experimentation is actually not an effective choice for experienced entrepreneurs because they learn less from the process. For future research, it will be important to understand if this finding is representative of the biased perception of resource providers or if it indicates a reality of the entrepreneurial process.

Early-stage entrepreneurs and potential resource providers face a common set of uncertainties in this fluid stage of entrepreneurship. While planning and experimentation have long been thought of as ways to handle uncertainty in entrepreneurship, this study highlights that they can also help make common cause between the entrepreneur and potential early-stage resource providers. Consistent with ample anecdotal evidence, these resource providers value descriptions of the activities in the process of entrepreneurship. They do not reward all entrepreneurs equally, however. Experimentation is most prized among inexperienced entrepreneurs, and is not rewarded among those with prior experience. Planning activities, on the other hand, are valued independent of the background of the entrepreneur. Thus, the study also calls attention to the fact that the appropriate entrepreneurial process may well vary with the background and experience of the individual entrepreneur.

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2.9. Online appendix

2.9.1. Details of the coding technique adopted to detect the presence of words related to planning, experimentation and both in the project descriptions

Figure 1 explains the coding process, which follows the procedure described by Short et al. (2010) but adds some additional steps to reduce the shortcomings of this technique.

Figure 1. Description of the coding process utilized, adapted from Short et al. (2010)

Step 1	Identification of a formal definition of planning and experimentation from literature on early-stage entrepreneurship
Step 2	Assessment of key components of planning/experimentation based on review of the literature (key components of the construct)
Step 3	Development of an exhaustive list of words that identify the key constructs of interest
Step 4	Validation of these lists with external raters (calculating inter-rater agreement)
Step 5	Performing initial keyword search using the list validated by the raters
Step 6	Refinement of the word list through manual screening of results of keyword search
Step 7	Modifying the search algorithm and text sample to reduce false positives/false negatives

We started by identifying a formal definition of planning and experimentation from literature on early-stage entrepreneurship (Step 1). Planning has been defined as "the process by which the entrepreneur, in exploiting an opportunity, creates a vision of the future and develops the necessary objectives, resources, and procedures to achieve that vision" (Sexton and Bowman-Upton, 1991, p. 118). A literature review (Step 2) on this topic showed that this early definition captured the two critical dimensions of planning: goals and a roadmap to achieve such goals. Work in this area supported a conceptualisation of planning based on a clear vision of what entrepreneurs wish to achieve, often described as a goal (Delmar and Shane, 2003; Shane and Delmar, 2004), and an articulation of the steps to achieve such goals (Bhidè, 2000; Shane and Delmar, 2004). With regards to experimentation, meanwhile, we did not find a clear definition of the construct, despite its growing relevance in the entrepreneurial context. We therefore elaborated on Lindholm-Dahlstrand et al. (2016) and defined experimentation as the process by which the entrepreneur tries out, selects and retains new ideas, methods or activities. Research in this area shows that while there is a range of activities that can be conducted when using an experimental approach, typically entrepreneurs follow a process classified as either trial and error (McGrath, 1995; Murray and Tripsas, 2004) or as more purposeful or scientific (Murray and Tripsas, 2004; Camuffo et al., 2018).

Having identified and developed two core dimensions for each construct, we then created a list of words traditionally associated with these dimensions (Step 3). In doing so, we started from words used in the literature to describe planning- or experimentation-related activities and include all relevant synonyms identified using the 'synsets' function in Python. This list is presented in Table 10 and Table 11 below.

Table 10. Concept dimensions and related words: planning

Concept dimension	Words identified
Clear goals	'goal', 'target', 'targeting', 'targeted', 'agenda', 'purpose', 'aim', 'aiming', 'aimed', 'aspire', 'aspiring', 'aspired', 'end point', 'objective'
Articulation of steps	'plan', 'planning', 'planned', 'schedule', 'scheduling', 'scheduled', 'program', 'programme', 'programming', 'programmed', 'map out', 'mapping out', 'mapped out', 'road map', 'scenario', 'forecast', 'forecasting', 'forecasted', 'foretell', 'foretelling', 'foretold', 'account', 'estimate', 'estimated', 'estimating', 'breakdown', 'time buffer', 'timescale', 'timetable' 'predict', 'predicting', 'predicted',

	‘prediction’, ‘scheme’, ‘schema’, ‘outline’, ‘outlining’, ‘outlined’, ‘blueprint’

Table 11. Concept dimensions and related words, experimentation

Concept dimension	Words identified
Trial and error attempts	‘trial and error’, ‘trial run’, ‘tryout’, ‘attempt’, ‘attempting’, ‘attempted’
Purposeful experimentation	‘experiment’, ‘experimenting’, ‘experimented’, ‘experimentation’, ‘prototype’, ‘prototyping’, ‘prototyped’, ‘test’, ‘testing’, ‘tested’, ‘hypothesis’, ‘hypotheses’, ‘hypothesizing’, ‘hypothesized’, ‘draft’, ‘drafting’, ‘drafted’, ‘mockup’, ‘mock-up’, ‘pilot’

We then provided four raters with a definition of planning and experimentation and asked them to read the word list associated with each concept and remove words that do not represent the dimensions identified in the literature. We also asked them to add any missing words that represent these dimensions (Step 4). Two raters were research assistants working on a project related to entrepreneurial experimentation and were unaware of the details of this study; one rater was a scholar working on text analysis, who was also unaware of the details of this study; and one rater was a native speaker (unlike the other raters). We calculated interrater agreement using the formula recommended by Short et al. (2010):

$$PA = 4A / Na + Nb + Nc + Nd$$

where PA is the proportion of agreement observed, A is the number of agreements between the raters, and Na, Nb, Nc and Nd are the number of words coded by each rater. The proportion of agreement observed is equal to 0.82. The general rule of thumb, as indicated by Riffe et al. (2005), is that coefficients above 0.75 indicate high reliability.

In step 5, we performed a keyword search using code written using the NLTK function in Python and the list of words validated by the raters. The Python code performed some basic pre-processing (lowercasing all words, removing punctuation and stopwords) before searching the text in each project description for the pre-specified keywords. We generated three binary variables (one for planning, one for experimentation, one for hybrid) equal to 1 if the keyword is present in a sentence of the project description and equal to 0 otherwise. For each project description, we also reported a count of the sentences containing keywords related to planning, experimentation, or hybrid approaches. We therefore created both binary and continuous measures of planning/experimentation, or hybrid approaches.

We followed Short et al. (2010) in using an approach that relies on keyword search. Results from well-structured keyword searches can produce accurate results (McKenny et al., 2016) and build on an established stream of research in psychology (Pennebaker et al., 2003) that is based on the assumption that the words used in narrative texts provide valuable insight related to the thought processes of the writer. Nevertheless, we acknowledge that keyword searches come with a certain degree of measurement error, and for this reason we performed additional steps to quantify and address its shortcomings. In step 6, we went through large samples of sentences to quantify the extent to which false positives occur and identify ways to reduce these false positives. The occurrence of false positives was low for project descriptions that contain words related to experimentation. We found 29 out of 1081 sentences (2.7%) from a randomly drawn sample that contain words present in the word list, but that did not actually refer to experimentation. As an example, the dictionary for purposeful experimentation included the word ‘test’; however, the sentence: “The consumer is then offered a free eye test and free fitting of their new frame along with the option to collect in store” is not related to experimentation. We solved this issue by modifying our search algorithm and excluding the bigram ‘eye test’ from project descriptions prior to the keyword search.

With regards to planning, meanwhile, there were more instances of false positives, mostly because when entrepreneurs mention ‘goals’ in a project description, they often refer to their Kickstarter goal (for fundraising). For this reason, we excluded from project descriptions bigrams such as ‘Kickstarter goal’, ‘stretch goal’ and ‘funding goal’, which result in several false positives. Finally, we also checked for the occurrence of false negatives by manually screening 100 project descriptions from a randomly drawn sample (10,247 sentences). We identified eight sentences that might refer to planning without using words from the key list. These sentences included ‘my dream is’, ‘our mission is’, ‘we want to’ and ‘this is the reason why’. The interpretation of these sentences appeared ambiguous, as they might refer to aspirations and ambitions rather than goals. For this reason, we opted for their exclusion as their inclusion would have resulted in an increase in false positives.

2.9.2. Details of Online Study One

This section provides details for the online experiment conducted on Prolific in October 2018 and described as ‘Study One’ in the manuscript. All participants started by being shown an introductory section that contained information about the fictitious company (Crowd Innovation Lab) conducting a study on Prolific. The section also contained a basic attention check to minimise the chance of random responses, as reproduced below.

Introductory section (shown to all participants and including attention check)

Crowd Innovation Lab invests in innovative products seeking funds through crowdfunding platforms. These are typically small and new companies that offer the possibility to pre-purchase their products through these crowdfunding platforms. Our team handpicks promising projects and assesses their desirability before investing in them.

Your opinion is important to us and through this survey, you will help us decide whether to provide financial support for this particular project or not.

We ask you to carefully read each section before answering the corresponding questions in the section. The survey includes eight questions and should take approximately five minutes.

Before you start, we would like to make sure you are going to read this description carefully. Please select ‘High level’ to indicate you are reading questions carefully:

- ○ Very high level
- ○ High level
- ○ Moderate level
- ○ Low level
- ○ Very low level

Manipulation: Five different conditions

The study included five different conditions to account for the variety of scenarios that backers might face on Kickstarter. More specifically, we included one condition where the entrepreneur described experimental activities, one condition where the entrepreneur described planning-related activities, one condition where the entrepreneur described a mixture of planning and experimentation, one with neutral words and one with no description of activities, as detailed below.

<u>Condition One: Description of experimental activities</u>

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night’s sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

The story behind Whole Pillow: Like any great idea, Whole Pillow started with an experiment. After a few sketches on a piece of paper, we created a prototype that was later tested in our laboratory. Through several trials, we found the perfect fabric to make our pillow from. Our laboratory tests showed that muslin lets air breathe through these products very easily, while making them hygienic. We are proud that our experimental approach to development has yielded a better alternative to the high-tech, modern methods of pillow making.

Condition Two: Description of planning activities

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

The story behind Whole Pillow: Like any great idea, Whole Pillow started with a plan. Following a careful timetable, we took steps to create in our factory a product that embodied our vision. Our main goal was to find the perfect fabric to make our pillow from. Muslin was a great solution because we envisioned a fabric that lets air breathe through these products very easily while making them hygienic. We are proud that our careful planning has yielded a better alternative to the high-tech, modern methods of pillow making.

Condition Three: Description of both planning and experimental activities

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

The story behind Whole Pillow: Like any great idea, Whole Pillow started with an experiment and a plan. Following a careful timetable, we created a prototype. Through several trials, we reached our goal to find the perfect fabric to make our pillow from. Muslin was a great solution because we envisioned a fabric that lets air breathe through these products very easily while making them hygienic. We are proud that our careful experiments and planning have yielded a better alternative to the high-tech, modern methods of pillow making.

Condition Four: No description of entrepreneurial activities, with neutral words instead

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

The story behind Whole Pillow: Like any great idea, Whole Pillow started with several activities. After finding a location for our factory, we created a product that later became Whole Pillow. The idea behind the product was to find the perfect fabric to make our pillow from. Muslin was a great solution because it is a fabric that lets air breathe through these products very easily while making them hygienic. We are proud that our company offers a better alternative to the high-tech, modern methods of pillow making.

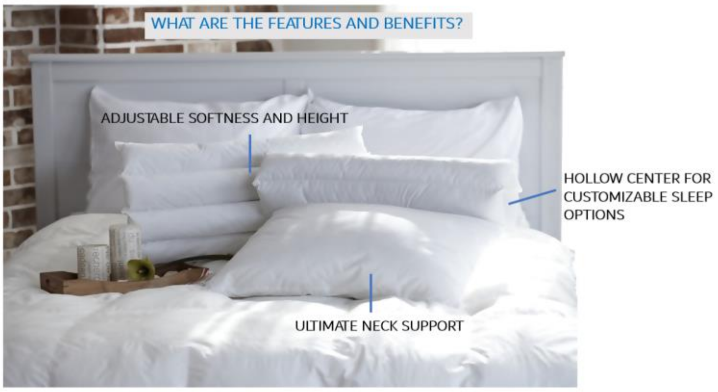
Condition Five: No description of entrepreneurial activities, no words

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

After this introductory text, all participants were shown a more detailed description of Whole Pillow, after which we asked several questions to measure their willingness to provide financial resources to Whole Pillow, as detailed below.

The key features of Whole Pillow are:

- adjustable softness and height of the pillow
- customizable pillow options
- guaranteed high level of safety and hygiene of the pillow
- smooth, soft and pleasant feel of the pillow cover



Given what you have read about Whole Pillow, are you interested in investing in this project?

○ Yes

○ No

How likely would you be to purchase Whole Pillow if it were available on the market today?

○ Definitely would

○ Probably would

○ Might or might not

○ Probably would not

○ Definitely would not

There are several packages for Whole Pillow. Which one would you choose from the options below?

- ◯ 69 euros for one pillow
- ◯ 79 euros for one pillow with a pillowcase
- ◯ 99 euros for two pillows
- ◯ 149 euros for two pillows with two pillowcases
- ◯ I would not want to purchase Whole Pillow

Participants completed the survey by reporting their gender, age, education level and prior experience with crowdfunding or other investments (such as bitcoin or stocks). This information confirmed that the randomization resulted in balanced groups.

2.9.3. Details of Online Study Two

The study described in the manuscript as 'Study Two' closely follows the structure of Study One. All participants started by being shown an introductory section that contained information about the same fictitious company used for Online Study One (Crowd Innovation Lab). The section also contained a basic attention check, as detailed below:

Crowd Innovation Lab invests in innovative products seeking funds through crowdfunding platforms. These are typically small and new companies that offer the possibility to pre-purchase their products through these crowdfunding platforms. Our team handpicks promising projects and assesses their desirability before investing in them.

Your opinion is important to us and through this survey, you will help us decide whether to provide financial support for this particular project or not.

We ask you to carefully read each section before answering the corresponding questions in the section. The survey includes eight questions and should take approximately five minutes.

Before you start, we would like to make sure you are going to read this description carefully. Please select 'High level' to indicate you are reading questions carefully:

○ Very high level

○ High level

○ Moderate level

○ Low level

○ Very low level

If participants provide a satisfactory answer to the attention check question, they are randomly assigned to one of the four conditions of this study: description of experimental activities for project creators with no experience, description of experimental activities for project creators with experience, description of planning activities for project creators with no experience, or description of planning activities for project creators with experience. In this case, the manipulation was highlighted both in the description of the project and in the picture representing Whole Pillow, reproducing how project creators present themselves on Kickstarter, as detailed below.

<u>Condition One: Description of experimental activities for unexperienced project creators</u>

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

Whole Pillow is our first crowdfunding project. Like any great idea, Whole Pillow started with an experiment. After a few sketches on a piece of paper, we created a prototype that was later tested in our laboratory. With several trials, we found the perfect fabric to make our pillow from. Our laboratory tests showed that muslin lets air breathe through these products very easily, while making them hygienic. We are proud that our experimental approach to development has yielded a better alternative to the high-tech, modern methods of pillow making.

How likely is it that the project creator has the knowledge needed to carry out this project?

◯ Extremely unlikely

◯ Quite unlikely

◯ Neither unlikely nor likely

◯ Quite likely

◯ Extremely likely

The key features of Whole Pillow are:

- adjustable softness and height of the pillow
- customizable pillow options
- guaranteed high level of safety and hygiene of the pillow
- smooth, soft and pleasant feel of the pillow cover

<u>Condition Two: Description of experimental activities for experienced project creators</u>

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

Whole Pillow is our third crowdfunding project. Like any great idea, Whole Pillow started with an experiment. After a few sketches on a piece of paper, we created a prototype that was later tested in our laboratory. With several trials, we found the perfect fabric to make our pillow from. Our laboratory tests showed that muslin lets air breathe through these products very easily, while making them hygienic. We are proud that our experimental approach to development has yielded a better alternative to the high-tech, modern methods of pillow making.

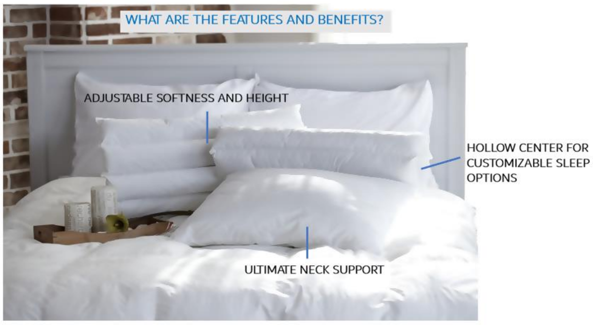
How likely is it that the project creator has the knowledge needed to carry out this project?

- ◯ Extremely unlikely
- ◯ Quite unlikely
- ◯ Neither unlikely nor likely
- ◯ Quite likely
- ◯ Extremely likely

The key features of Whole Pillow are:

- adjustable softness and height of the pillow
- customizable pillow options
- guaranteed high level of safety and hygiene of the pillow
- smooth, soft and pleasant feel of the pillow cover

B Pillow, Project creator
Project number 3



<u>Condition Three: Description of planning activities for unexperienced project creators</u>

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

Whole Pillow is our first crowdfunding project. Like any great idea, Whole Pillow started with a plan. Following a careful timetable, we took steps to create in our factory a product that embodied our vision. Our main goal was to find the perfect fabric to make our pillow from. Muslin was a great solution because we envisioned a fabric that lets air breathe through these products very easily while making them hygienic. We are proud that our careful planning has yielded a better alternative to the high-tech, modern methods of pillow making.

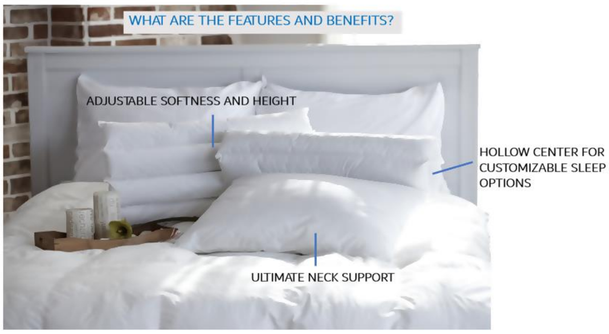
How likely is it that the project creator has the knowledge needed to carry out this project?

- ◯ Extremely unlikely
- ◯ Quite unlikely
- ◯ Neither unlikely nor likely
- ◯ Quite likely
- ◯ Extremely likely

The key features of Whole Pillow are:

- adjustable softness and height of the pillow
- customizable pillow options
- guaranteed high level of safety and hygiene of the pillow
- smooth, soft and pleasant feel of the pillow cover

B Pillow, Project creator
Project number 1



<u>Condition Four: Description of planning activities for experienced project creators</u>

Whole Pillow is a pillow with a hole in the centre to offer you a wholesome night's sleep. It is a multifunctional pillow that allows you to store your phone, books, and all your bedtime accessories without sacrificing comfort to your head and neck.

Whole Pillow is our third crowdfunding project. Like any great idea, Whole Pillow started with a plan. Following a careful timetable, we took steps to create in our factory a product that embodied our vision. Our main goal was to find the perfect fabric to make our pillow. Muslin was a great solution because we envisioned a fabric that lets air breathe through these products very easily while making them hygienic. We are proud that our careful planning has yielded a better alternative to the high-tech, modern methods of pillow making.

How likely is it that the project creator has the knowledge needed to carry out this project?

- ◯ Extremely unlikely
- ◯ Quite unlikely
- ◯ Neither unlikely nor likely
- ◯ Quite likely
- ◯ Extremely likely

The key features of Whole Pillow are:

- adjustable softness and height of the pillow
- customizable pillow options
- guaranteed high level of safety and hygiene of the pillow
- smooth, soft and pleasant feel of the pillow cover

In the rest of the study, we collect the same information across the different conditions with the goal of testing the mechanism behind the choices of resource providers. We do so by using five-point Likert scales and items related to market, founder and project uncertainty, as explained in the manuscript. We conclude the study by collecting basic demographic information, as detailed below.

To what extent do you think there is a market for Whole Pillow?

- Not at all
- To a little extent
- To some extent
- To a moderate extent
- To a great extent

How likely is it that the pillow will live up to the description in the project?

- Extremely unlikely
- Quite unlikely
- Neither unlikely nor likely
- Quite likely
- Extremely likely

How likely is Whole Pillow to be funded?

- Extremely unlikely
- Quite unlikely
- Neither unlikely nor likely
- Quite likely
- Extremely likely

Given what you have read about Whole Pillow, are you interested in investing in this project?

- Yes
- No

How likely would you be to purchase Whole Pillow if it were available on the market today?

- ○ Definitely would
- ○ Probably would
- ○ Might or might not
- ○ Probably would not
- ○ Definitely would not

There are several packages for Whole Pillow. Which one would you choose from the options below?

- ○ 69 euros for one pillow
- ○ 79 euros for one pillow with a pillowcase
- ○ 99 euros for two pillows
- ○ 149 euros for two pillows with two pillowcases
- ○ I would not want to purchase Whole Pillow

We concluded the study by asking participants to report their gender, age, education level and prior experience with crowdfunding or other investments (such as bitcoin or stocks). This information confirmed that the randomization resulted in balanced groups.

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3.

Small Changes with Big Impact: Experimental Evidence of a Scientific Approach to the Decision-Making of Entrepreneurial Firms

(Joint with Arnaldo Camuffo and Alfonso Gambardella)

Abstract

Identifying the most promising business ideas is key to the introduction of novel firms, but predicting their success can be difficult. We argue that if entrepreneurs adopt a scientific approach by formulating problems clearly, developing theories about the implications of their actions, and testing these theories, they make better decisions. Our theory predicts that the scientific approach corrects the problem of overestimation and underestimation of the returns from business ideas. This has implications for important entrepreneurial choices, such as discontinuing a business idea and pivoting, as well as for performance. Using a field experiment with 251 nascent entrepreneurs attending a pre-acceleration program, we examine the effect of a scientific approach to decision-making. In the field experiment, we teach the treated group to formulate the problem scientifically and to develop and test theories about their actions, while the control group follows a standard training approach. We collect 18 data points on the decision-making and performance of all entrepreneurs for 14 months. Results show that treated entrepreneurs are more likely to close their start-up. We also find that scientific entrepreneurs are more likely to pivot a small number of times, suggesting that the scientific approach makes them more precise in pivoting to more valuable ideas. Finally, we find that the scientific approach increases revenue, suggesting that a more accurate assessment of ideas helps entrepreneurs to make better decisions and eventually leads to better performance. This study shows that the scientific approach is a critical link between decision-making and performance of nascent entrepreneurs.

Keywords: scientific approach, entrepreneurship, field experiment.

3.1. Introduction

The biggest initial challenge entrepreneurs face is to identify a feasible and profitable business idea to turn into a new venture. The process of idea identification tends to be ‘incoherently chaotic and focused on the future’ (Eisenhardt and Brown, 1998, p.35) and happens through iterations based on the feedback entrepreneurs obtain from peers (Chatterji et al., 2019), early customers (Parker, 2006), experts in the field and sponsors (Cohen et al., 2018), or even family and friends (Bennett and Chatterji, 2017). This process of idea identification is crucial because initial choices on the direction in which the idea should develop will determine if it can become a fully-fledged start-up (Aldrich and Martinez, 2015) and in the long run can greatly constrain or enable the performance of these firms (Dimov, 2007).

History is full of cases where entrepreneurs significantly changed the business idea they initially identified, as they realized that their original intuition was unlikely to work. Twitter, for instance, was conceived as Odeo, a platform that simplified the search for and subscription to podcasts. As iTunes started to gain popularity in the podcast space, Odeo turned into Twitter, a micro-blogging platform. This iteration represented a radical change in strategy (a ‘pivot’), which allowed the owners to avoid a costly mistake. Similar radical changes also marked the early days of successful tech companies such as Instagram, Lyft, PayPal, Pinterest, Slack and YouTube. All these pivots required entrepreneurs to understand what elements of their business ideas were likely to work and in which direction they should turn.

Extant studies on this topic converge on the iterative nature of the process entrepreneurs go through as they evaluate and develop their business ideas (Baron and Ensley, 2006), but do not clarify how this process of strategic change and pivoting should be conducted. Emerging streams in entrepreneurship such as effectuation (Sarasvathy, 2001) and bricolage (Baker and

Nelson, 2005) propose that entrepreneurs should rely on non-predictive techniques given the high uncertainty surrounding the creation of a new venture. Proponents of these approaches argue that entrepreneurs should 'make do' with what they have at hand and improvise to win over stakeholders that will co-create new products and markets with the entrepreneur (Wiltbank et al., 2006). Effectual and bricolage approaches are attempts to acknowledge the bounded rationality of the entrepreneur and embrace the uncertainty of the environment by setting aside predictions and focusing on controlling the environment. Other scholars suggest, instead, that structured and disciplined processes of idea evaluation and development can mitigate fallible judgement (Hogarth and Karelaia, 2012) and reduce the cognitive biases that affect entrepreneurial decision-making (Murray and Tripsas, 2004; Camuffo et al., 2019; Cohen et al., 2018; Kahneman et al., 2019).

Drawing on the latter stream of research, we propose that entrepreneurs can better understand whether their business idea is valuable when they formulate problems clearly, develop theories about the implications of their actions, and test these theories rigorously. In conducting these actions, labelled 'a scientific approach to decision-making', entrepreneurs also become better equipped to gather and interpret valuable signals from customers and other stakeholders that contribute to pivots of the initial business idea (Furr, 2009; Gans et al., 2016; Camuffo et al., 2019). Our theory also discusses the implications of this approach for entrepreneurial action by contrasting two 'stylized ideal types' of entrepreneurs ('confused' or 'unimaginative') and using such a distinction as a conceptual device to illustrate the different ways in which the scientific approach might affect how entrepreneurs assess and change their business ideas.

In this study, we provide evidence of the impact of a scientific approach to entrepreneurial decision-making by conducting a field experiment with 251 nascent entrepreneurs attending a pre-acceleration program. In our study, we randomly assign entrepreneurs to either a treatment (being taught how to use a scientific approach when developing a business idea) or a control group (being taught how to develop a business idea). We then collect detailed data about their performance and decision-making over 14 months to investigate how a scientific approach impacts the development of these business ideas. We find that treated entrepreneurs are more likely to close their business than entrepreneurs in the control group, and that they exhibit patterns of pivoting consistent with the idea that they are more precise in changing business direction. We also find that they make higher revenue than entrepreneurs in the control group. Taken together, our results are consistent with the idea that the scientific approach corrects the problem of overestimation and underestimation of the returns from business ideas.

We begin in Section 2 by *clarifying* what a scientific approach to entrepreneurial decision-making means. Section 3 provides initial evidence of how a scientific approach affects entrepreneurs' decisions, using graphs to capture different patterns in the behavior of the treatment and control groups. The goal of this section is to offer an intuitive representation of the effect of the adoption of a scientific approach on entrepreneurial decisions and behavior. Moreover, we answer the recent call of many scholars to 'show the data' in order to display where regression results come from and mitigate the emphasis on regression estimates and p-values in the interpretation of results (Halsey et al., 2015; Bettis et al., 2016; Goldfarb and King, 2016; Starr and Goldfarb, 2018; Greve, 2018; Levine, 2018). Section 4 articulates the paper's theory and formulates three research propositions. Our theory – further elaborated in the Appendix, which includes a model that explains more formally the logic of our analysis – offers a plausible explanation for the patterns we observe in our data. The research design, data and methods are illustrated in Section 5. Section 6 uses a variety of regression analyses and other robustness checks to provide additional evidence of how the adoption of a scientific approach affects entrepreneurial decisions in ways consistent with our propositions. Section 7 highlights some limitations, implications and potential development directions of this research.

3.2. A scientific approach to decision-making

A key feature of nascent entrepreneurship is that returns from business ideas are extremely skewed and their quality is hard to assess. Acquiring knowledge about the potential outcomes of a business idea can reduce this fundamental uncertainty (Delmar and Shane, 2003; Dencker et al., 2009), because it generates information about the ultimate value of a business idea. We propose that a scientific approach to decision-making can reveal more precise information and lead to better estimates of the value of a business idea.

Extant literature suggests there are two fundamental types of decision-making in early-stage entrepreneurship. The first type is akin to trial and error (Dencker et al., 2009), and it normally involves experimenting sequentially with various methods until entrepreneurs achieve some results. This search strategy is normally 'blind' or only guided by prior assumptions and beliefs, and consequently entrepreneurs often run the risk of engaging in confirmatory search (Shepherd et al., 2012). An alternative approach to decision-making that entrepreneurs can take is a more systematic and structured one, which has been called purposeful (Murray and Tripsas, 2004), or scientific (Camuffo et al, 2019). We define this scientific approach as a discipline, a set of behavioral routines – similar to those used by scientists – that the entrepreneurs follow to discover the value of their ideas and develop them. This discipline can be taught and learned, and comprises four major components:

1. The articulation of a 'theory' (Zenger, 2016), which typically leads to the definition of a business model as grounded on correctly framing the customer problem the founding team

wishes to solve. Scientist entrepreneurs treat customer problems as research questions and formulate theories about them that are novel, simple, falsifiable and generalizable (Felin and Zenger, 2009 and 2017).

2. The explicit formulation of hypotheses that are composed from the 'theory' and enable the entrepreneurs to bring it to reality. Hypotheses are educated guesses about the customers, their problems, etc. They are testable and falsifiable inasmuch as they clearly define the contingencies in which they are not false (or are definitely false) and can produce good, actionable evidence and validated learning (Eisenmann et al., 2011).

3. The empirical testing of the hypotheses, through rigorous data collection and analysis and, possibly, through experiments (Murray and Tripsas, 2004; Kerr, Nanda, & Rhodes-Kropf, 2014). These tests need to be rigorous, and evidence- or data-driven. They use valid and reliable metrics. They allow us to identify causal relationships (experimental or quasi-experimental designs) (Davenport, 2009).

4. The open, critical and independent analysis and interpretation of the outcomes of the tests. The honest and thorough evaluation of the evidence gathered testing hypotheses requires both individual and collective judgement (Pfeffer and Sutton, 2006), as well as critical appraisal of evidence. Openness to questioning, discussion and criticism is a crucial part of entrepreneurial decision-making, as it is in science (Rousseau, 2006).

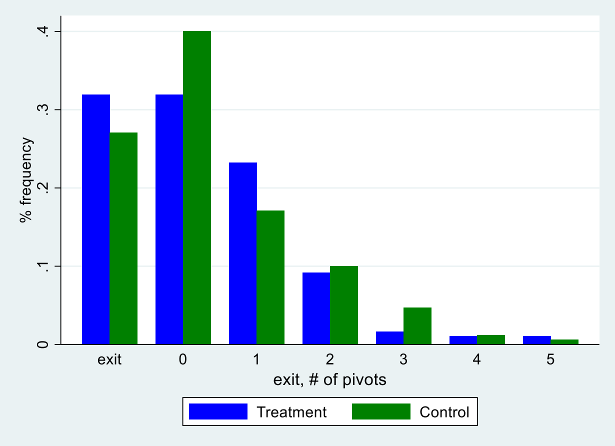
Bennet and Chatterji (2017) and Camuffo et al. (2019) provide evidence that the majority of entrepreneurs do not 'naturally' behave in a scientific manner. We expect that entrepreneurs who 'discipline' their decisions according to this approach will make better predictions of the value of their business idea, and will act accordingly, as detailed in the next section.

3.3. Our findings at a glance: a preliminary representation of the treatment effects

Before we present our theory, we show our raw data. The goal is twofold. On the one hand, we want to display basic patterns in the data. On the other hand, we use these patterns to build our theory, which we illustrate in the next section. In this section, we define our variables and data broadly for the purpose of this preliminary discussion. Section 5 provides more details about our data, the variables we use, and the design of the experiment.

Figure 4 summarizes whether the 251 start-ups that attended our pre-acceleration program abandoned the business (*exit*), or changed some important elements of it (*pivot*) such as the core value proposition of the business or the target customers, during the 14 months (66 weeks) in which we followed them. The figure distinguishes between the 126 start-ups in the treatment group, which we exposed to training that included the adoption of a scientific approach to decision-making, and the 125 start-ups in the control group, which we exposed to similar training of equal time and intensity, but without the focus on the scientific approach. Quite a few start-ups that exited during our time frame pivoted before they exited. Figure 4 then includes the pivots of the start-ups that exit later on. However, the histograms remain qualitatively similar if we exclude the start-ups that exit.

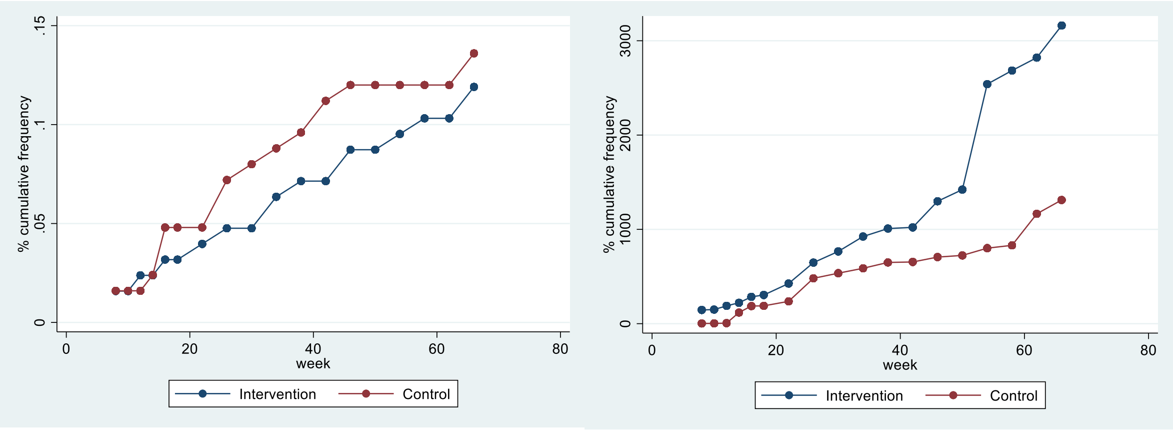
Figure 4. Frequency of exits, # of pivots



The first column in Figure 4 represents the number of start-ups that exited during our time frame. As the figure shows, more start-ups in the treatment group exited than in the control group (59 vs 46). This finding, which confirms what Camuffo et al. (2019) found in a smaller-scale randomized control trial, is counterintuitive because we would expect that the scientific approach would increase the success of a business. The following columns show the number of start-ups, in the treatment and control group, that pivoted from 0 up to 5 times during the analyzed period. Fewer start-ups in the treatment group pivoted 0 times (59 vs 68 – column 2). This means that treated start-ups tend to stick to their initial idea less than their counterparts. This is consistent with the fact that not only do treated start-ups exit more, but they also pivot one time more frequently than controls (43 vs 29 – column 3). Interestingly, while the number of start-ups in the treatment and control group that pivoted two times is the same (17), fewer start-ups in the treatment group pivoted three or more times (7 vs 11). These patterns suggest that the scientific approach helps entrepreneurs see new opportunities they can pivot to; however, once they see a new business opportunity, they tend to stick to it, as if they are more precise in seeing good opportunities to which they can pivot.

Figure 5 (left graph) shows the effect of the scientific treatment on performance, using revenue as a proxy. This graph reports the cumulative shares of start-ups that in each week start generating revenue. The figure shows that start-ups in the control group are more likely to start generating revenue earlier. This is intriguing as it suggests that the start-ups treated with the scientific approach do not start making revenue earlier, and it indicates that a scientific approach does not speed up the process of commercialization of the products that start-ups offer. Figure 5 (right graph) reports, instead, on the average cumulative revenue in each week of the start-ups in the treatment group compared to that for the control group. This average includes start-ups that generate zero revenue. Treated start-ups systematically generate a higher average cumulative revenue. This is a result with important implications, suggesting that a scientific approach leads to a more successful (though not quicker) commercialization of the products start-ups offer. These graphs suggest that start-ups in the treatment group move more cautiously and take more time to generate revenue than control start-ups. However, based on this initial revenue data, they seem to be able to focus on more profitable ideas.

Figure 5. Cumulative % of start-ups that begin earning revenue, weeks 8-66 (left) and average cumulative revenue, weeks 8-66 (right)



Thirty-three start-ups in our sample make revenue during the time frame of our experiment. This is unsurprising given that these entrepreneurs enter the pre-acceleration program with just a business idea, and we observe their performance for 14 months. Of these start-ups, 17 are in the treatment group and 16 in the control group. This provides further evidence that the effect of the treatment is not to raise the odds of a start-up successfully making more revenue. In fact, it squares with the result about exit in that the treatment seems to mostly have an effect on the tails of the analyzed sample distribution – more exit, higher average revenue conditional on making revenue. To summarize, the preliminary evidence illustrated in this section highlights three patterns of behavior in treated entrepreneurs: 1) they are more likely to exit (abandon their business idea) than entrepreneurs in the control group; 2) they do not pivot more than the control group, but they are more likely to pivot once or twice, and less likely to pivot zero or many times; 3) they generate revenue later than the control group, but they generate higher revenue on average.

3.4. Theory

3.4.1. Building blocks

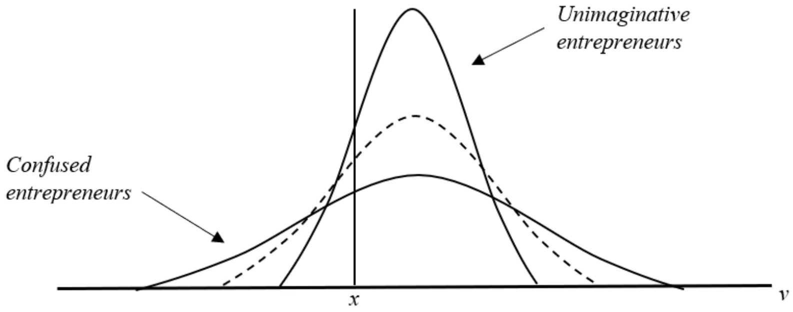
We focus on entrepreneurs who, at least to some extent, base their decisions on predictions. In particular, they evaluate the attractiveness and potential returns of their business idea by predicting a performance variable. It is not easy to nail down how entrepreneurs think, particularly when they consider starting a new business and have to make early decisions such as product-market fit, the business model, or more generally the identity of their firms. Some scholars or practitioners argue that they ‘just do it’ or follow patterns such as effectuation (Sarasvasthy, 2001), pattern recognition (Baron and Ensley, 2006), bricolage (Baker and Nelson, 2005) or other routines or heuristics. However, in general, entrepreneurs combine thinking and doing (Ott et al., 2017) that involves some form of prediction, even if coarse and unrefined. Moreover, they are more likely to make predictions when the decision is important. Even the entrepreneurs in our trial, who operate in relatively simple businesses (such as retail and e-Commerce), tend to use predictions to make important decisions – albeit possibly in fuzzy ways, and in combination with other elements.

In our framework, entrepreneurs predict the net value of a business idea, which we call v. They do not observe this value when they have to make the decision whether to commit to develop their business idea. Thus, the way they form this prediction is important. Even when the predictions are coarse or unrefined, they are the result of a process in which entrepreneurs attempt to identify what factors or variables affect the performance of the idea and use these variables to make the prediction. However, entrepreneurs do not clearly understand which variables matter. Moreover, they may consider some variables but not others, or they may consider more variables than needed, and they do not predict exactly the impact of these variables on performance. The prediction v is then determined by a set of random variables. For simplicity we set v to be the sum of these variables – for example, entrepreneurs think that the prediction depends on five variables, $v = v_1 + v_2 + v_3 + v_4 + v_5$.

Although entrepreneurs do not observe v when they make the decision, they know that if they commit to the idea and develop it, they will gain more information about v, and will eventually observe it. As a result, when entrepreneurs decide whether to develop the idea, they know that they will not make returns lower than an opportunity cost x that they will realize with certainty if they discontinue the development of the idea. Therefore, entrepreneurs predict that they earn v if $v \geq x$ and x if $v < x$.

As Figure 6 shows, this implies that a probability distribution of v with fatter tails generates a higher expected value than a distribution with slimmer tails. This is because high realizations of v occur with higher probabilities than the distribution with slimmer tails; conversely, the negative realizations that make the fatter distribution less appealing do not occur because entrepreneurs realize x instead of the low realizations of v to the right of x. The variability of v is then crucial, and this paper argues that the scientific approach affects this variability. However, in order to understand the effect of the scientific approach on the breadth of the distribution of v, we first focus on the sources of this variability.

Figure 6. Probability densities of 'confused' and 'unimaginative' entrepreneurs



Densities have the same mean. Conditional on $v \geq x$ → confused entrepreneurs perceive higher expected value and unimaginative entrepreneurs perceive lower expected value. Scientific approach → both distributions converge towards the dashed distribution.

Some entrepreneurs have clearer ideas, which we represent by saying that they predict v using fewer components, for example $v = v_1 + v_2 + v_3$ instead of $v = v_1 + v_2 + v_3 + v_4 + v_5$. This stems from the fact that some entrepreneurs are able to predict the impact of some variables with more certainty. The simplest way to describe it is that they believe that the impact of some variables is zero, and therefore these variables do not affect v. A more general representation is that some entrepreneurs realize, for example, that v_3, v_4 and v_5 are highly correlated. They tend to move together and thus the impact of one variable is enough to understand how these three variables affect v. This is equivalent to three collinear variables in a linear regression. The estimated coefficients satisfy some constraint, and it is possible to estimate the impact of the three variables by using only one variable. More broadly, this means that some entrepreneurs are unable to focus on a key set of independent variables that affect v. They do not disregard variables whose explanatory power to v is negligible after including some more fundamental variables in their framework. We call these entrepreneurs 'confused' because they are unable to select the fundamental variables that affect *v*. The less relevant variables they include in their framework make their prediction noisier. Other entrepreneurs may not see that *v* is made up of a larger set of independent variables. For example, they believe that *v* only depends on v_1, and do not see that v_2 and v_3 also matter. These entrepreneurs do not understand that the variability of *v* is higher. We label them as 'unimaginative' because they neglect some important factors that affect *v*.

The addition of stochastic components with the same mean to a sum of stochastic components generates an aggregate distribution with the same mean and fatter tails (Rothschild and Stiglitz, 1970), such as in Figure 6. For simplicity, we assume that the perceived distributions of our entrepreneurs have the same mean and differ only in terms of their variability. In other words, we assume that the constraints in the impact of a subset of the variables, which makes the distribution slimmer, or the addition of new important variables, which makes the distribution fatter, has no effect on the means of the distributions. This is reasonable because the effects produced by an increase or a reduction in the number of components could be positive or negative and may cancel out on average. Moreover, this assumption is not a crucial one and we will clarify its implications in our discussion whenever it is relevant to do so. Therefore, confused entrepreneurs, who are unable to select few relevant variables that determine *v*, perceive distributions in which extreme realizations at both ends occur with higher probability. Conversely, unimaginative entrepreneurs, who are unable to see that some other variables affect *v*, perceive distributions with slimmer tails.

As an example of our representation, the founders of Airbnb, Brian Chesky and Joe Gebbia, considered starting a new business based on a simple proposition: hotels and similar accommodations are expensive in San Francisco, and homeowners can offer comparable stays for guests at a fraction of the price. They decided to go ahead with their business when three guests booked an air mattress in the living room of their apartment through a website they created. However, at that stage, they did not know whether a scaled-up version of their business idea could work. They were confused in the sense that v was the sum of many variables that could affect the scaling up of the business. Nonetheless, the fatter-tail distributions produced by the many uncertain components of v, combined with the opportunity cost x, produced sufficiently high expectations to continue. Later, they struggled to get reservations and for months their business did not grow. As they began to understand why this had happened, some of the components of v got clarified, making the distribution slimmer and possibly reducing the expected returns. Based on this new prediction, they had to make another decision and reconsider whether to continue with their business. By gathering feedback on those who booked accommodations, they understood that a crucial factor for the success of their business was establishing trust. This added a new component to v. The uncertainty stemmed from the fact that they had alternative ways to address the problem. However, the recognition of this new component made the distribution more imaginative. The fatter tails resurrected the possibility that the business could produce high returns, and encouraged them to continue.

As the current success of the business suggests, the realization of this uncertainty was positive. However, this is less important for the purpose of this discussion. What matters for us are the two decisions about whether to continue with the business before the founders resolved the market uncertainty associated with it. In the first decision, the confused distribution prompted them to continue. In the second decision, the additional component ‘trust’ had a similar effect. By making the distribution more imaginative, it prompted Airbnb founders to continue in spite of the negative signal they had received in the first few months of operation.

3.4.2. How the scientific approach corrects entrepreneurial judgement

The scientific approach corrects the judgements of confused and unimaginative entrepreneurs. Theory and tests, applied to the assessment of the idea, help confused entrepreneurs to focus on the key independent variables that determine v, or help them to see more precisely the impacts of these variables. In line with our representation of the problem, an entrepreneur might develop a theory suggesting, for instance, that v_3, v_4 and v_5 are highly correlated and can be combined in one variable. She might then conduct a set of tests and corroborate this conjecture. Theory and tests can also help unimaginative entrepreneurs to uncover other variables that determine v. For instance, problem-framing and feedback from users enabled the founders of Airbnb to see that trust, a variable they had not taken into account, matters.

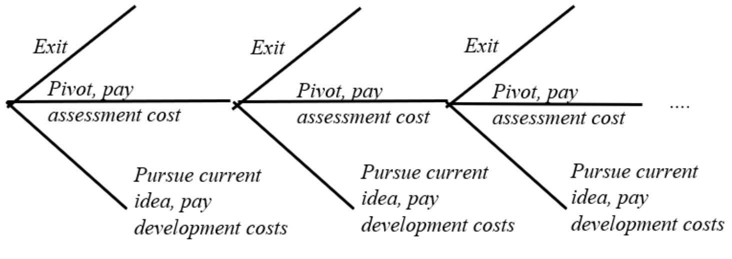
It is hard to say a priori whether theory and tests make entrepreneurs less confused or more imaginative. However, the assumption we make in this paper is that when entrepreneurs think there are many unexplained factors that affect v, theory and tests are more likely to reveal more precisely the impact of these variables. When, instead, entrepreneurs choose very few variables, the scientific approach is more likely to reveal new variables. Simply put, the scientific approach makes a confused entrepreneur less confused and an unimaginative entrepreneur more imaginative. As shown in Figure 6, this implies that the scientific approach makes the distribution of expected outcomes narrower in the case of confused entrepreneurs and wider in the case of unimaginative entrepreneurs. This lowers the expectations of returns in the former case, and raises them in the latter case.

3.4.3. Implications of the scientific approach for exit, pivot, and performance

The scientific approach has implications for exit, pivot, and performance. In order to discuss these implications, we refer to Figure 7, that represents the early stage decision of entrepreneurs.

Typically, entrepreneurs evaluate new business ideas using cycles (Hampel et al., 2019). Because of resource limitations, they assess one idea at the time (Gans et al., 2019). In each cycle, they work on an idea to understand its business potential. However, during the process, they might come up with other ideas. At the end of each cycle, they decide whether to exit, pivot to a new idea, or commit to the current idea, which is the decision we focus upon in this paper. If the prospect of the current and future ideas is slim, they exit; if one of the new ideas is promising, they abandon the current idea and switch to the new one. If they commit, they invest in the current idea to develop it. If entrepreneurs exit or commit to the current idea, the exploration process ends; if they pivot, such process continues until they exit or commit. In each cycle, entrepreneurs pay a cost to explore the idea, and when they develop an idea, they pay a development cost; if they exit, they do not pay any development cost. Thus, when they decide to exit, pivot, or commit, they have paid the exploration cost of the current idea, but they have not paid the exploration cost of the new idea they can pivot to, or the development cost of the current idea. As discussed by Gans et al. (2019), after entrepreneurs pivot, they cannot retrieve the idea they left behind. In our framework, exit is different from failure, which may occur if - after committing to an idea - the entrepreneur realizes that it is not profitable. Since we focus on the early-stage decision, we do not refer to the ultimate failure or success of the start-up.

Figure 7. Pivoting cycles and their costs



The implication of a scientific approach for exit is straightforward. The scientific approach reduces the prediction range of confused entrepreneurs and raises the prediction range of unimaginative entrepreneurs. If we compare scientific entrepreneurs with their counterfactual non-scientific entrepreneurs, the scientific approach makes it more likely that confused entrepreneurs will abandon their business ideas. This is because theory and tests make their predictions more accurate, showing that some of the variability that they perceived does not exist in practice. Therefore, they can switch from positive to negative predictions, but not the other way around. At the same time, the scientific approach makes it less likely that unimaginative entrepreneurs will exit. Theory and tests help them to understand what new factors affect the expected value of their business idea, which raises the odds that they might enjoy higher realizations at the higher end of the distribution. Thus, they switch from negative to positive predictions, but not the other way around.

On average, adoption of the scientific approach will then increase or decrease the number of start-ups that abandon their business ideas according to the relative proportion of 'confused' or 'unimaginative' entrepreneurs. Current evidence suggests that entrepreneurs tend to perceive their ideas as more valuable than they actually are, as shown by the high failure rate of start-ups (Fairlie and Miranda, 2017), excess entry (Camerer and Lovallo, 1999) and other analyses of the perception of entrepreneurial returns (Astebro, 2002; Cain et al., 2015). Therefore, if on average entrepreneurs overestimate the values of their business ideas, the scientific approach ought to increase the share of exits, which is consistent with the data we presented in the previous section. Our assumption that the scientific approach does not affect the mean of the distributions is not crucial. If the scientific approach increased the mean of the distribution, both confused and unimaginative entrepreneurs would be less likely to exit. Still, if we observe that the scientific approach increases exit, our theory suggests that this must be because most entrepreneurs are confused. We state our first proposition as follows:

> **Proposition 1.** *If most entrepreneurs overestimate the value of their idea, the scientific approach is more likely to reduce the expected value of their ideas, increasing the share of entrepreneurs that exit; the opposite will be true if entrepreneurs underestimate the value of their idea.*

With regards to pivoting, entrepreneurs compare the current idea with the new idea. The new idea is more uncertain because entrepreneurs have studied the current idea for some time, which has reduced uncertainty. This also raises differences in the perception of the new idea vis-à-vis the current idea. Lack of imagination or confusion can be traits of the entrepreneurs or of the domain that they explore. As a matter of fact, entrepreneurs explore in similar domains or activities; for instance, the new idea could be related to a variation of the original product, or it could be offered to a different market. Whatever the reason, lack of imagination affects both the current and the new idea, and so does confusion. For example, by working on the current idea for some time, unimaginative entrepreneurs understand aspects of it that were unclear when they started exploring. In particular, as they understand the current idea better, and they assess it, they may see determinants of its value that they were unable to see before exploring, and become more imaginative about it. Similarly, confused entrepreneurs are unable to select important determinants. After they explore, they reduce confusion about the current idea. Of course, this does not eliminate uncertainty about the current idea. Moreover, as we discussed, the scientific approach helps decision-makers to correct lack of imagination and confusion to a greater extent. The point we make here is simply that this correction arises, in part and to a lesser extent, just from exploring and understanding the idea better. In contrast, uncertainty about the new idea looms larger. Unimaginative entrepreneurs are then relatively more unimaginative about the new idea than the current idea. Similarly, confused entrepreneurs are relatively more confused about the new idea compared to the current idea.

As discussed earlier, lack of imagination, which implies inability to see important determinants, implies that entrepreneurs perceive a lower value of the idea. As a result, if unimaginative entrepreneurs are more imaginative about the current than the new idea, they are less likely to pivot because they perceive a relatively higher value of the current idea with respect to the new one. Confused entrepreneurs are less likely to be confused about the current idea because of the exploration they did, and they are more likely to be confused about the new idea they did not explore. Since greater confusion raises the perceived prospects, confused entrepreneurs are, instead, more likely to pivot.

The scientific approach reduces these differences in perception of the current and new idea between different types of entrepreneurs, or different entrepreneurial projects. As we said, entrepreneurs tend to search in the same domain. Over the search cycles, they learn about this domain, which implies that they learn about common elements that link current and new ideas. In turn, this means that if unimaginative entrepreneurs become more imaginative thanks to theory and tests, they are likely to learn more about potential determinants of the new idea as well. Thus, unimaginative entrepreneurs become more imaginative about the current idea because of the exploration they did; however, the unimaginative entrepreneurs who adopt a scientific approach, which corrects their lack of imagination, realize the common elements between the current and the future idea, know how to link them, and therefore they become more imaginative about the new idea as well. As a result, the adoption of the scientific approach raises the relative value of the new idea with respect to the current one. The unimaginative scientific entrepreneurs are then more likely to pivot than the unimaginative non-scientific entrepreneurs.

Consider now the case of confused entrepreneurs. Like in the previous case, exploring the current idea substitutes - in part – for the scientific approach. This makes the assessment of the current idea of non-scientific and confused entrepreneurs more similar to the scientific and confused entrepreneurs. This difference is instead more pronounced for the new idea that does not benefit from the levelling off generated by exploring. Thus, non-scientific and confused entrepreneurs perceive a relatively higher potential of the new idea vis-à-vis the current idea compared to confused entrepreneurs that adopt the scientific approach. The former are then more likely to pivot than the latter.

Overall, this implies that the scientific approach reduces the difference between the perceived value of the current and new idea between unimaginative and confused entrepreneurs. Assuming that there are both unimaginative and confused entrepreneurs, the scientific approach makes it more likely that unimaginative entrepreneurs pivot, and less likely that confused entrepreneurs pivot. If we rule out exit because the current idea is good enough, then, following the sequence of cycles of Figure 7, confused entrepreneurs are the most likely to pivot at each stage. Therefore they exhibit the highest number of pivots across cycles. Unimaginative entrepreneurs are the least likely to pivot at each stage, and exhibit the least number of pivots. Scientific entrepreneurs are in between: they pivot a few times but not many times. Specifically, confused entrepreneurs who adopt the scientific approach are less likely to pivot at each stage than the counterfactual confused entrepreneurs who do not adopt the approach: therefore, the former entrepreneurs pivot fewer times than the latter entrepreneurs. Unimaginative entrepreneurs who adopt the scientific approach are more likely to pivot than the counterfactual unimaginative entrepreneurs at each stage: therefore the former entrepreneurs pivot more times than the latter entrepreneurs.

If the scientific approach increase the mean of the distributions, then irrespective of whether entrepreneurs are unimaginative or confused, both the current and new idea will generate higher returns. As we discussed earlier, this process affects exit, but it is unclear how it affects the decision to pivot because it does not produce a clear indication of whether the current and new idea change to a different extent. We would need to make assumptions about the changes across search cycles produced by the impact of the scientific approach on the expected value of the ideas. If we do not make these assumptions, we can conclude that the main drivers of the decision to pivot are the lower variability of the current idea, and the lower difference on the variability of the current vis-à-vis the new idea produced, the use of a scientific approach, and the characteristics of the entrepreneurs (or the domain of the problem). We state our second proposition as follows.

Proposition 2. *Entrepreneurs who adopt the scientific approach are likely to pivot a few times but unlikely to pivot many times.*

So far, we have been agnostic about whether the scientific approach generates better predictions. The logic we discussed simply states that the scientific approach narrows the perception of excessively wide distributions and widens the perception of excessively narrow distributions of expected returns. Wide or narrow distributions do not correspond to worse or better predictions, per se. However, a corollary of Propositions 1 and 2 is that the scientific approach should improve performance. In fact, at a minimum, if we assume that the scientific approach does not have any effect on the development of the business idea and that there is no heterogeneity in development capabilities (or that these are randomly distributed), scientist entrepreneurs should perform better on average. This is because, having assessed their ideas better, they avoid pursuing or pivoting to less promising ideas (if confused), or they pursue or pivot to ideas that did not initially look promising enough but that turn out to be so (if unimaginative). Our third proposition is as follows:

> **Proposition 3.** *Entrepreneurs adopting the scientific approach will enjoy higher revenue than non-scientist entrepreneurs because they will avoid pursuing less promising ideas (if 'confused') or they will pursue more promising ideas (if 'unimaginative').*

3.5. Research design

3.5.1. The randomized control trial

Our research embeds a field experiment into a pre-acceleration program, or a 'start-up school' that provides training to early-stage entrepreneurs for short periods of time. This type of program represents an ideal setting for our enquiry because it selects and trains entrepreneurs that only have a business idea and have yet to undertake significant steps to bring their product or service to the market. Moreover, administering our treatment through training is a suitable choice because training programs have been shown to affect outcomes for treated entrepreneurs (Anderson et al., 2018; Campos et al., 2018).

Participants in our program are early-stage entrepreneurial firms, which are defined as those run by founders in the process of starting a business (Bosma et al., 2012). We issued a call for applications using multiple online (blogs, online communities) and offline channels (magazines for entrepreneurs, events), resulting in a total of 272 applications, out of which we selected into the intervention 258 start-ups. Seven start-ups abandoned the program before its start, so our final sample consisted of 251 participants. We used a statistical software package (Stata) to randomly assign each start-up to one of the two arms of the experiment (treatment and control groups)[3]. We checked that the treatment (126 start-ups) and control groups (125 start-ups) were balanced on a number of key covariates that might affect the absorption of the intervention and its subsequent outcomes. Table 12 presents the results of these randomization checks, confirming that the two arms of the experiment are balanced on key characteristics such as demographic variables (age, highest education level, work experience of the entrepreneurial team), industry, founding team size and composition, effort, and the expected performance and subjectively estimated value of the business idea. Given the number of checks, we are confident that the randomization was successful.

[3] We opted for pure randomization with balance checks, as this was, in our case, a better strategy than stratified randomisation. Choosing the appropriate strata among these variables to implement stratified randomisation and to allocate the participants to the treatment and control groups was not obvious from a theoretical standpoint.

Table 12. Randomization checks on key covariates

Variables	Treatment		Control		Difference	
	Mean	Sd	Mean	Sd	Coefficient	P-value
Start-up potential	47.35	21.23	47.21	23.31	-0.14	(0.96)
Local	0.57	0.47	0.57	0.46	0.00	(0.98)
Sector experience	2.84	3.80	2.35	3.63	-0.49	(0.30)
Start-up experience	1.08	2.18	0.94	1.45	-0.15	(0.53)
Management experience	2.25	3.68	2.29	4.19	0.04	(0.94)
Work experience	8.69	7.71	9.08	8.86	0.39	(0.71)
Working hours	10.35	9.96	11.02	11.47	0.67	(0.62)
Full time	0.56	0.43	0.61	0.42	0.05	(0.37)
Part time	0.09	0.18	0.08	0.17	-0.01	(0.87)
Males	0.72	0.38	0.75	0.36	0.03	(0.52)
Age	31.40	8.15	31.47	7.90	0.07	(0.94)
Team size	2.24	1.46	2.29	1.37	0.05	(0.76)
Probability to stay	31.16	32.50	32.20	31.68	1.04	(0.80)
Top education	2.94	0.74	2.95	0.80	0.01	(0.95)
Months to revenue	11.46	5.80	11.45	5.84	-0.01	(1.00)
Minimum value	45.43	19.83	42.99	22.90	-2.43	(0.37)
Maximum value	85.04	16.19	85.56	16.18	0.52	(0.80)
Analytic thinking	8.36	3.65	8.06	3.30	-0.30	(0.50)
Intuitive thinking	4.08	1.68	3.85	1.74	-0.23	(0.29)
Observations	126		125		251	

Following best practices (Baird et al., 2016), we pre-registered this randomized controlled trial on September 15, 2017. The intervention took place at the end of September 2017 and finished in December 2017 with the 251 participants attending a training program designed by the research team. Our pre-acceleration program focuses on market validation, with a series of activities aimed at testing the desirability of a product or service concept against a potential target market. These activities provide suitable information to help entrepreneurs assess the potential of their business ideas and are frequently taught in pre-acceleration programs. In order to offer engaging lessons and a valuable learning experience to participants, we divided the treated and control groups into smaller groups that were randomly matched with seven experienced instructors, recruited and trained for the purpose of this study. Since each instructor was teaching one group of treated entrepreneurs and one group of control entrepreneurs, we organized several 'train-the-trainer' sessions and conducted tests and simulations with the instructors to make sure that instructors were able to deliver the training material in accordance with our experimental design. We ensured that the instructors trained the start-ups in each group using the exact same content by providing all training material ourselves, and by attending the lectures as observers.

The course comprised eight sessions (for a total of 24 hours of training), and the content and duration of each session was the same for both groups. Both the treatment and control groups learnt about tools that are widely used in entrepreneurial education (such as the Business Model Canvas, and Minimum Viable Product). However, the treatment group was taught how to use each of these tools using a scientific approach. Throughout the training program, treated start-ups were taught to elaborate a theory behind their choices, and to articulate hypotheses and test them rigorously. The control group, meanwhile, did not learn about the scientific approach, but followed the traditional approach to market validation used by entrepreneurs, which often relies on trial-and-error techniques. We took a number of measures to ensure the internal validity of our results and the soundness of our experiment. We avoided contamination by teaching treated and control start-ups in different time slots of the same day (morning and afternoon) to prevent them from meeting and discussing key elements of the treatment. For the same reasons, we kept communications about the program separate and discrete for the two groups.

3.5.2. Data collection procedure

We collected detailed information on all the participants with an extensive pre-intervention survey, which we used to randomly assign participants to treatment and control groups and to assess the pre-intervention levels of a number of covariates. During and after the intervention, we collected 18 data points through telephone interviews, following Bloom and Van Reenen’s (2010) approach. Telephone interviews usually lasted for 30 minutes and were conceived as open-ended conversations with entrepreneurs. To guide these conversations, we created an interview protocol for interviewers. In the first part of the interview, entrepreneurs were asked to report changes in the entrepreneurial team and describe the activities they had been conducting in the last two weeks. Using an approach similar to qualitative interviews, we let key themes emerge from entrepreneurial narratives. However, research assistants were instructed to code the content of the interview for the frequency of occurrence of themes related to scientific decision-making using non-leading questions. In the second part of the telephone interview, we asked entrepreneurs to self-report their performance, as well as to provide estimates of the value of their idea. In collecting this information, we were also able to observe entrepreneurs who abandoned their business idea altogether or who decided to pivot to a different one. The first telephone interview took place eight weeks after the training program had begun. We then collected data every two weeks until week 18 (the training program ended in week 12), and every four weeks until week 66. Our panel dataset includes 4518 observations for 251 firms over 18 periods.

3.5.3. Measures

Dependent variables

In order to accurately capture the events that unfolded in the first 14 months of activity of the entrepreneurs that participated in the program, we collected multiple measures of performance and outcomes of interest, as detailed below.

- *Exit* – We regularly ascertained through telephone interviews if entrepreneurs had abandoned the program and/or ceased activities related to their start-up. We coded this event into a binary variable that takes the value 0 until the firm exits (abandons the program and ceases the start-up), 1 in the time period over which the firm exits, and a missing value thereafter. To avoid attrition biases, we checked that the entrepreneurs who informed us of their decision to discontinue their initiative had truly abandoned their activity. We found that 20 start-ups left the course but continued to develop their business ideas, while 105 abandoned their ideas as well. We kept the 20 start-ups that abandoned the course in our sample to preserve the balance checks between treatment and control, but we did not count them as start-ups that exited. When we remove these start-ups from the sample, the treatment and control groups are still balanced, and in general the results of our analyses are not qualitatively different.

- *Pivot* – Through the telephone interviews we collected detailed information about the activities conducted by entrepreneurs and the changes they made to their business ideas during the observation period. In the first session of the course, we taught entrepreneurs to use a Business Model Canvas (BMC), a visual representation of the core aspects of their business. As entrepreneurs were taught to use this tool and keep it updated, we were able to keep track of the changes that they made in relation to nine key business elements (value proposition, customers, channels, customer relationships, key partners, key activities, key resources, costs and revenue streams). We considered a pivot as a major change in the business model – that is, if the entrepreneur moved from the original idea to another idea that changed the core value proposition of the business or its target customers. Our start-ups pivoted from zero to five times in our time frame, and we recorded the week in which the pivot took place.
- *Revenue* – During each telephone interview, we collected the cumulative revenues generated by each start-up. To obtain the flow of revenue between two periods we subtracted one amount of revenue from another over two contiguous periods. Understandably, not all firms in our sample reached the revenue stage in the 66-week

observation window. In particular, 33 of the 251 start-ups produced some revenue in this period; 16 of these firms were in the treatment group and 17 in the control group.

Independent variable

The main independent variable is *Intervention*, a dummy variable taking a value of 1 for start-ups in the treatment group and 0 for those in the control group. We also computed another variable, *Cumulative Intervention*, which takes values 1-4 for the treatment group in the four periods in which the treatment is ongoing, and 4 in the following periods. The variable is equal to zero in all periods for the control group. Finally, *Postintervention* is equal to 1 for the treatment group after the treatment (from period five on) and 0 in the first four periods, and in all periods for the control group. We present all our results using *Intervention*, but our results remain the same when we use *Cumulative Intervention* or *Postintervention* as the independent variable. We use these alternative specifications as robustness checks, and we do not report them for brevity's sake.

We also show results using *Scientific Intensity*, a measure of the level of adoption of the scientific approach derived from the content analysis of the telephone interviews. *Scientific Intensity* is a time-varying score (ranging from one to five) that captures the level of adoption of the scientific approach. In order to calculate this score, a team of research assistants analyzed and coded each interview's content according to a pre-defined coding scheme. This scheme includes themes and behavioral indicators of the adoption of the four components of the scientific approach (theory, hypotheses, tests and evaluation) that quantify the extent to which entrepreneurs are scientific in their decision-making process, as detailed in the Online Appendix. Through this scheme, we obtain an overall additive score of the level of adoption. Even if we created coding guidelines and extensively trained the team of research assistants through examples that create solid reference points, *Scientific Intensity* remains a subjective measure. To assess the reliability of the coding, we randomly selected a sample of interviews that underwent double coding with multiple research assistants who were not aware of the allocation of entrepreneurs to the treatment or control group. Additional analysis (not reported for brevity's sake) shows that there is generally agreement between multiple coders.

While a basic premise behind this study is that entrepreneurs can learn to think and act like scientists in developing their business ideas, we are aware that the extent to which they use scientific thinking largely depends on endogenous characteristics. Even the random allocation to either a treatment or a control group might not be enough to resolve all endogeneity concerns related to this issue. For this reason, we use *Intervention* as an instrument for *Scientific Intensity*. The rationale is that *Intervention* is completely exogenous in this setting and allows us to quantify the extent to which our treatment induced an exogenous change in scientific entrepreneurial thinking. In the 2SLS regressions in which we use *Scientific Intensity*, we also employ *Hours Worked* as a control for the fact that the treatment may affect the intensity of the start-up activities (entrepreneurs' effort). *Hours Worked* is a self-reported measure collected during the telephone interviews; it quantifies the total number of hours worked by the entrepreneurial team in each observation period. The length of the observation period differs for some of the interviews, as detailed at the beginning of Section 3.5.2. However, all our regressions include time dummies that take into account differences in the lengths of the observation periods. Table 13 defines all the variables that we use in our analyses and reports descriptive statistics.

Table 13. Variable definitions and descriptive statistics

	Variable definition	N	MEAN	SD	MIN	MAX
	Cross-section					
Exit	Dummy=1 if start-up exits, 0 otherwise	251	0.418	0.494	0	1
Week of Exit	Week of exit of the start-up	251	51.139	20.984	8	66
Pivot	Number of pivots	251	0.813	1.059	0	5
Pivot1	Dummy=1 if start-up pivots 1 time, 0 otherwise	251	0.287	0.453	0	1
Pivot2-5	Dummy=1 if start-up pivots 2 to 5 times, 0 otherwise	251	0.207	0.406	0	1
Pivot1-2	Dummy=1 if start-up pivots 1 or 2 times, 0 otherwise	251	0.422	0.494	0	1
Pivot3-5	Dummy=1 if start-up pivots 3 to 5 times, 0 otherwise	251	0.072	0.259	0	1
Week of 1st Pivot	Week of 1st pivot	251	39.817	27.857	8	66
Week of 2nd Pivot	Week of 2nd pivot	251	56.446	19.866	10	66
Week of 3rd Pivot	Week of 3rd pivot	251	63.139	11.150	12	66
Revenue	Revenue in week 66 in euros	251	2240.4	13212.2	0	150000
Week of Revenue	Week in which start-up starts making revenue	251	61.554	13.313	8	66
Intervention	Dummy=1 for treated start-ups, 0 for control	251	0.502	0.501	0	1
Scientific Intensity	Index of scientific intensity (average per start-up over time)	251	2.406	1.174	0	5
Hours Worked	Hours worked between two periods (average per start-up over time)	251	12.912	14.427	0	120.658
	Panel					
Exit	Dummy=1 on the week of exit, 0 otherwise, missing after exit	3196	0.033	0.178	0	1
Pivot (dummy)	Dummy=1 on the week in which the start-up pivots, 0 otherwise	4518	0.045	0.208	0	1
First Pivot	Dummy=1 on the week in which the start-up makes the 1st pivot, 0 otherwise, missing after the 1st pivot	2632	0.047	0.212	0	1
Second Pivot	Dummy=1 on the week in which the start-up makes the 2nd pivot, 0 otherwise, missing after the 2nd pivot	3865	0.013	0.115	0	1
Third Pivot	Dummy=1 on the week in which the start-up makes the 3rd pivot, 0 otherwise, missing after the 3rd pivot	4331	0.004	0.064	0	1
Revenue (flow)	Flow of revenue in each period (in euros)	4518	122.25	1595.56	0	65000
Scientific Intensity	Index of scientific intensity (1-5)	4518	2.406	1.225	0	5
Hours Worked	Hours worked between two periods	4518	13.035	19.108	0	280

3.6. Regression analysis

3.6.1. Exit

We begin by looking at the regression results of the effect of our intervention on exit in Table 14.

Table 14. Exit

VARIABLES	Exit OLS (Cross-Section)	Exit Probit (Cross-Section)	Exit OLS (Panel)	Exit Probit (Panel)	Week of Exit Survival
Intervention	0.103**	0.266**	0.053***	0.126**	0.294**
	(0.026)	(0.011)	(0.003)	(0.045)	(0.031)
Constant	0.382***	-0.300***	0.081***	-1.621***	-
	(0.000)	(0.001)	(0.000)	(0.000)	
Observations	251	251	3,196	3,196	251
R-squared	0.030	-	-	-	-
Dummies for mentors	Yes	Yes	Yes	Yes	Yes
Time FE	-	-	Yes	Yes	-
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor
Number of id			251		

Robust p-values in parentheses *** p<0.01, ** p<0.05, * p<0.1

The first two columns of Table 14 report our cross-section results. They are, respectively, the results of a linear probability model and a probit model. The dependent variable is a binary one and equal to 0 if the start-up did not exit, and to 1 if the start-up abandoned the business during our observation window. The regressions include dummies for the instructors who taught the training program to account for differences in teaching styles across instructors. We cluster the errors of the regressions by intervention and instructor. The next two columns report the results of a panel analysis of the 251 start-ups during the 18 periods of data collection. Along with dummies for instructors and errors clustered by intervention and instructor, the panel includes time-fixed effects. Finally, the last column of Table 14 shows a survival regression that predicts the time of exit. This regression also includes instructor dummies, and the errors are clustered by intervention and instructor. Consistently with Proposition 1, Table 14 shows that the intervention makes exit more likely. In all the regressions of Table 14, exit increases with intervention, and the estimated coefficients display a low p-value. The survival regression shows that the intervention raises the odds that start-ups exit at any moment in time.

In terms of effect sizes, our intervention increases the probability of exit by 10% in the cross-section. This is a sizable effect given that scientist entrepreneurs exit earlier. To appreciate what this might mean, consider the following cases. At an individual level, these results imply that one entrepreneur out of ten could avoid wasting time, money and effort developing business ideas that are not as promising as they initially thought they were. At an institutional level, consider an accelerator with a capacity of 100 start-ups, monthly intakes of ten start-ups and a one-year program to accelerate start-ups. The adoption of the scientific approach as an 'accelerating philosophy' could improve the time to acceleration, freeing up a considerable amount of resources (roughly more than 10% without considering faster turnover). This derives from the fact that 'confused' entrepreneurs – of whom we assume a prevalence – exit more, allowing for a more efficient use of the accelerator resources.

3.6.2. Pivot

Proposition 2 states that treated start-ups are more likely to pivot a few times but less likely to do so many times. We again present cross-section and panel regression results regarding pivot.

We start with the cross-section in Table 15. All the regressions in this table use dummies for instructors, and they cluster errors by intervention and instructor. The first column of Table 15 presents the OLS results of the change in the total number of pivots produced by the intervention. As the results in the column show, the intervention does not affect the number of pivots. This is in line with Proposition 2, which states that treated start-ups are more likely to pivot a few but not many times. Since in our sample start-ups pivot between zero and five times, the next two columns of Table 15 show the linear probability models, using as dependent variables a dummy that takes the value 1 if the start-ups experience, respectively, one or one to two pivots, vis-à-vis zero and two to five, or zero and three to five pivots. In both cases, the effect of the treatment is sizable and statistically significant. Treated start-ups are more likely to pivot once or twice than zero times, or than two or three times. The last four columns of Table 15 estimate two multinomial probit models with three categories. The baseline category in both models, not shown in the table, is zero pivots. The other two categories in the first model are one and two to five pivots, while in the second model they are one to two and three to five pivots. As the table shows, the intervention raises the probability of the intermediate category vis-à-vis the other two extreme categories.

Table 15. Pivot (cross-section)

				Pivot = 0; 1; 2-5		Pivot = 0; 1-2; 3-5	
	Pivot	Pivot1	Pivot1-2	Pivot1	Pivot2-5	Pivot1-2	Pivot3-5
VARIABLES	OLS	OLS	OLS	Multinomial Probit	Multinomial Probit	Multinomial Probit	Multinomial Probit
Intervention	0.020	0.105***	0.104***	0.422***	-0.009	0.355***	-0.165
	(0.748)	(0.001)	(0.001)	(0.000)	(0.955)	(0.000)	(0.264)
Constant	1.017***	0.273***	0.436***	-0.392***	-0.312**	-0.020	-0.879***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.029)	(0.804)	(0.000)
Observations	251	251	251	251	251	251	251
R-squared	0.061	0.045	0.067	-	-	-	-
Dummies for Instructors	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor

In multinomial probit models the omitted regression is pivot = 0
Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 16 shows the results of a panel analysis of pivots. We employ four dependent variables. The first one is a dummy that is equal to one when a start-up pivots (any pivot) and equal to zero otherwise. *First Pivot*, *Second Pivot*, and *Third Pivot* are dummies that are equal to one when the start-up pivots, respectively, the first, second and third time, and zero otherwise. In these three regressions we drop the observations after the first, second or third pivot.

Table 16. Pivot (panel: OLS, Poisson)

VARIABLES	Pivot (dummy)	First Pivot	Second Pivot	Third Pivot
Intervention (OLS)	0.001	0.008**	-0.002	-0.002***
	(0.740)	(0.012)	(0.403)	(0.009)
Intervention (Poisson)	0.024	0.170**	-0.149	-0.465**
	(0.738)	(0.013)	(0.404)	(0.026)
Observations	4,518	2,632	3,865	4,331
Number of id	251	251	251	251
Dummies for Mentors	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

These three regressions explain whether the treatment affects the probability of observing one, two or three pivots. We use OLS and Poisson specifications instead of probit because there are certain weeks with no pivots, which probit would drop from our sample, and these include time dummies. We also ran survival regressions for the first, second and third pivot (which we do not report for brevity's sake, but which are available upon request), and these results are in line with those shown in Table 16. Overall, the results in Table 16 show that, consistently with Proposition 2, the treatment does not affect the probability of start-ups pivoting. However, the treatment positively affects the probability that entrepreneurs pivot once, and negatively affects the probability that they pivot a third time, while it has no effect on the probability that they pivot a second time. This suggests that the scientific approach makes it more likely that start-ups pivot once, and less likely that they pivot three or more times.

The effects sizes of the regressions are more complex to interpret in the case of pivot. However, going back to the examples discussed in the case of exit, at the individual level, more selective pivoting (fewer, better pivots) allows entrepreneurs to explore ideas that would otherwise be lost (foregone options). But it also brings about the opportunity to avoid wasteful pivoting, saving significant amounts of time, money and effort. At the institutional level, acceleration programs could be more effective and efficient – redundant pivoting could be reduced by as much as 80% (one pivot instead of five).

3.6.3. Performance

Our theory predicts that the scientific approach improves start-ups' performance (Proposition 3). The adoption of the scientific approach improves the accuracy of entrepreneurs' predictive models, drives better assessment of their ideas and reduces the probability of incurring false positives (pursuing an idea whose value is overestimated) or false negatives (abandoning an idea whose value is underestimated). For this reason, and even assuming that the adoption of the scientific approach has no effect on the development stage (which is a very conservative assumption), scientist entrepreneurs should, on average, develop better ideas and, hence, perform better. Table 17 reports the cross-section and panel results of the differential in revenues attributable to the treatment. All these regressions include dummies for instructors, and the errors are clustered by intervention and instructor. The results show that the adoption of the scientific approach has a sizable effect on revenue, and that this effect is statistically significant.

Table 17. Performance

VARIABLES	Week of Revenue Survival	Revenue OLS (Cross-section)	Revenue (Flow) OLS (Panel)
Intervention	-0.093	1,679.216*	89.052*
	(0.757)	(0.090)	(0.072)
Constant	-	-348.051	95.849
		(0.514)	(0.493)
Observations	251	251	4,518
R-squared		0.026	
Dummies for mentors	Yes	Yes	Yes
Time FE	-	-	Yes
Clustered Errors	Intervention	Intervention	Intervention
	Instructor	Instructor	Instructor
Number of id			251

Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

The first column of Table 17 reports the results of a survival regression where the dependent variable is the failure event, which is the first week in which the start-up generates revenue. The treatment has no effect, i.e. scientific entrepreneurs do not obtain revenue earlier than non-scientists. The next two columns (cross-section and panel) show that scientific entrepreneurs generate, on average, higher income. As already mentioned in Section 3.3, in our sample only 33 firms produce revenue, 16 in the treatment group and 17 in the control group. These are reasonable numbers given that nascent entrepreneurs normally take more than one year to produce revenue. Overall, it seems that, at least within the time frame of about one year of our RCT, the scientific approach neither induces more start-ups to make revenue, nor causes them to make revenue earlier. However, the start-ups that make revenue seem to make more revenue, which suggests that they have been able to tap into better business opportunities. Together with the greater probability of exit, and selective pivoting, the scientific approach seems to encourage entrepreneurs to make better decisions in the sense that they go after better opportunities or avoid bad opportunities.

In terms of effect sizes, the average effects obtained through the panel regressions in Table 17 (an average biweekly differential of approximately € 90 between treated and control start-ups) are small. However, Figure 5 provides an indication of what might be the magnitude of the treatment effect after approximately one year. Scientist entrepreneurs average three times the amount of cumulative revenue of non-scientists. Furthermore, the variation of scientist entrepreneurs is much higher than that of non-scientists, suggesting that the scientific approach, as stated in our third proposition, operates through better idea selection.

3.6.4. The intensity of adoption of the scientific approach and other robustness checks

Finally, we report the results of regressions that use our measure of *Scientific Intensity* instrumented by *Intervention* instead of the Intention-To-Treat (ITT) regressions that only use *Intervention*. The limitation of this analysis is that we make the ad-hoc exclusion restriction that *Intervention* only affects *Scientific Intensity* in the first stage. This assumes that our treatment does not have any direct effect on the dependent variables other than through *Scientific Intensity*. Another limitation is that, while we measure *Scientific Intensity* at the firm and time levels, *Intervention* only varies across firms. Thus, the regressions we show in this section are only cross-sections or survivals (no longitudinal analysis).

Overall, these regressions confirm the results of the ITT regressions. First and foremost, Table 18 shows that *Scientific Intensity* is correlated with *Intervention*. Table 19 shows clearly that *Scientific Intensity* makes exit more likely, and Table 20 shows equally clearly that *Scientific Intensity* makes start-ups more likely to pivot once or twice rather than never or three or more times, and that *Scientific Intensity* makes it more likely that the first pivot occurs earlier, while later pivots occur later. Finally, Table 21 shows that *Scientific Intensity* raises revenue. In this case, the statistical significance implies p-values higher than 10%, which can only be expected with an instrumental-variable regression compared to an ITT regression. Table 21 also shows that the number of hours worked by the start-up (*Hours Worked*) is not correlated with *Intervention*, and when used as a regressor together with *Scientific Intensity* in the revenue regression, it does not cancel the effect of *Scientific Intensity*. A potential alternative effect of our treatment is that it made entrepreneurs more energetic because the lectures or topics were more interesting and challenging. Table 21 suggests that this is not the case.

Table 18. First Stage Regression, Scientific Intensity with respect to Intervention

VARIABLES	Scientific Intensity
Intervention	0.308**
	(0.011)
Constant	2.431***
	(0.000)
Observations	251
R-squared	0.085
Dummies for Mentors	Yes
Clustered Errors	Intervention Instructor

Scientific Intensity = Average scientific intensity over the 66 weeks by firms
Robust pval in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 19. Exit, IV Regressions

VARIABLES	Exit 2SLS	Exit IV Probit	Week of Exit 2SLS
Scientific_Intensity	0.334**	0.567***	-15.640**
	(0.039)	(0.000)	(0.034)
Constant	-0.428	-1.572***	90.244***
	(0.315)	(0.000)	(0.000)
Observations	251	251	251
Dummies for Mentors	Yes	Yes	Yes
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor

Scientific Intensity = Average scientific intensity over the 66 weeks by firms
In Week of Exit regression, Scientific Intensity is the average up to the week of exit
Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 20. Pivot, IV Regressions

VARIABLES	Pivot (dummy) 2SLS	Pivot1 2SLS	Pivot1-2 2SLS	Pivot1 IV Probit	Pivot1-2 IV Probit	Week of 1st Pivot 2SLS	Week of 2nd Pivot 2SLS	Week of 3rd Pivot 2SLS
Scientific_ Intensity	0.064	0.341***	0.337***	0.744***	0.749***	-7.028**	2.660	2.275
	(0.725)	(0.003)	(0.006)	(0.000)	(0.000)	(0.048)	(0.522)	(0.189)
Constant	0.862*	-0.556*	-0.384	-2.257***	-1.971***	53.840***	44.299***	54.603***
	(0.067)	(0.065)	(0.232)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	251	251	251	251	251	251	251	251
Dummies for Mentors	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor

Scientific_Intensity = Average scientific intensity over the 66 weeks by firms
Week of 1st, 2nd, 3rd Pivot = Week in which the start-up carries out the 1st, 2nd, 3rd Pivot or 66 if the start-up does not pivot
In Week of Pivot regressions, Scientific_Intensity is the average up to the week of 1st,2nd or 3rd Pivot
Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 21. Revenue, IV Regressions

VARIABLES	Revenue 2SLS	Week of Revenue 2SLS	Hours Worked OLS	Revenue OLS	Revenue 2SLS
Scientific Intensity	5,449.554	2.651			5,657.445
	(0.114)	(0.531)			(0.132)
Intervention			-0.723	1,804.034	
			(0.678)	(0.121)	
Hours Worked				172.739*	88.652
				(0.079)	(0.241)
Constant	-13,593.297	57.761***	14.665***	-2,881.221	-15,398.642
	(0.130)	(0.000)	(0.010)	(0.119)	(0.111)
Observations	251	251	251	251	251
R-squared	-0.132	-0.066	0.040	0.060	-0.138
Dummies for mentors	Yes	Yes	Yes	Yes	Yes
Clustered Errors	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor	Intervention Instructor

Scientific_Intensity = Average scientific intensity over the 66 weeks by start-ups
In Week of Revenue, Scientific_Intensity is the average up to the week in which the start-up begins making revenue. Hours_Worked = Average hours worked over the 66 weeks by start-ups
Robust pval in parentheses *** p<0.01, ** p<0.05, * p<0.1

3.7. Discussion and conclusion

This study confirms and extends the evidence provided by Camuffo et al. (2019) about the positive effects of the adoption of a scientific approach in the assessment of entrepreneurial ideas. Research-wise, we offer a comprehensive theory about why and how adopting a scientific approach improves entrepreneurial predictions and judgement, highlighting how it works under different conditions. More specifically, we distinguish between two general types of entrepreneurs – those who cannot make precise predictions ('confused'), and those who do not see opportunities ('unimaginative'). In doing so, we highlight the flaws in their predictive models and in their assessment of entrepreneurial ideas, and we show how adopting a scientific approach can correct these flaws and lead to better decisions. We connect this line of reasoning to the current debate in entrepreneurship, highlighting how the scientific approach might be thought of as a 'rational heuristic' – a set of behavioral routines or a discipline that can mitigate decision biases (Zhang and Cueto, 2017) and improve the combination of thinking and doing that characterizes any entrepreneurial venture (Eisenhardt and Bingham, 2017; Ott et al., 2017).

From the standpoint of entrepreneurial practice, the adoption of a scientific approach can be beneficial for entrepreneurs, who can improve their decisions, mitigating the risk of incurring false positives and false negatives. We also believe the scientific approach can represent a way to reframe entrepreneurship education, at least in the early stages of entrepreneurial activity. Our intervention could represent a starting point to think about how to make some types of entrepreneurial training more effective. Finally, we believe that the adoption of the scientific approach could be beneficial for institutions that train, assist, support, mentor and accelerate entrepreneurial ventures. The scientific approach might represent a nice complement to other practices, such as peer or expert reviews, that have been proven to be successful and are conceptually consistent with a scientific approach (Cohen et al., 2018; Chatterji et al., 2019).

This study is also subject to limitations. As in most field experiments in social sciences, its design does not allow perfect identification. Given the high financial costs of running a similar field experiment, the sample size is limited, which limits the power of the experiment. However, the fact that we have repeated observation over a reasonably long period of time mitigates this problem and makes our findings more robust. Other limitations represent opportunities for extensions and directions for further research. An important point is that our theory is fundamentally a theory of precision or accuracy in the assessment of entrepreneurial ideas. However, while mitigating fallible judgement and biases is an important component of entrepreneurial decision-making, understanding decision-making dynamics and how entrepreneurs search and learn over time is also important. In this respect, an important open question stems from the fact that we observe that scientist-entrepreneurs are not more likely to make revenue or to make revenue earlier. Our sense, corroborated by the interviews and the direct observation of the participants, is that this derives from two factors. First, it reflects the fact that the adoption of the scientific approach is more demanding. Assessing an idea based on theory and tests requires one to think deeply, elicit hypotheses, collect data, design and run experiments, engage in critical analysis and ask for independent third-party opinions. All other things being equal, complying with the disciplined behavior required by the scientific approach inevitably slows down entrepreneurs, who therefore will not achieve revenue faster, despite their more accurate predictions. Second, it reflects the fact that scientist entrepreneurs, at least in our research setting, exit more and pivot more selectively. Indeed, non-scientists in the control group, who tend to continue with their original idea (and develop it), might achieve revenue earlier, on average.

We do find, however, that scientific entrepreneurs select more promising ideas, which generate, on average, higher income. Given that we randomized on the quality of ideas, it seems that the scientific approach equips treated entrepreneurs with ways of thinking and acting that allow them to select more promising ideas. At the same time, the fact that scientist entrepreneurs make higher revenue, on average, could also stem, at least in principle, from another mechanism, i.e. that the scientific approach allows them to generate, over time, better ideas. Extant literature (Ries, 2011; Furr & Dyer, 2014) explicitly conceptualizes pivoting as a strategic iteration as being a new idea in the neighborhood of the current idea. In our case, it might be that, through better thinking and doing, not only can scientist entrepreneurs better assess their current ideas, but they also have a higher probability of moving to a better idea. Unfortunately, in this study we do not have the data to investigate this potential mechanism (learning through pivoting across ideas).

Other limitations of our study represent opportunities for further research. For example, we sample Italian early-stage start-ups across regions and industries. We believe that the scientific approach might work differently under different contingencies (e.g. specific countries, regions, industries). We are not able to investigate such differences in this study, but they might be the object of interesting extensions. We are particularly intrigued by what the effect might be in situations where technologies (and technological innovations) play a particular role and when entrepreneurs are scientists or have a science background. Similarly, it would be interesting to observe the effect of the adoption of the scientific approach in the context of corporate entrepreneurship. Furthermore, our study uses an intervention embedded in a given learning model. It would be interesting to see under which teaching approach and learning model (e.g. more or less experiential, in presence or online, one-on-one mentorship-based versus team or class-based, etc.) the scientific approach exerts better effects. This would allow us to understand how to scale similar interventions with a view to improving entrepreneurship education, a priority for many policymakers who are looking to stimulate economic growth through entrepreneurship. Additionally, our study did not identify the micro-mechanisms that, at the individual level, drive the different perceptions and predictions of scientist entrepreneurs. There is a vast body of literature about the corrections of perceptions, changes in predictive models and mitigation of biases. However, we did not have the data to actually show what the mechanism is that, given an idea, leads scientist entrepreneurs to have different perceptions regarding the variability of its outcomes, compared to non-scientists.

Finally, it would be intriguing to evaluate the effects of the scientific approach vis-à-vis other approaches, corresponding to other entrepreneurship theories, such as effectuation. An interesting study could test if, to what extent, and under which conditions, non-predictive techniques – with entrepreneurs 'making do' with what they have to hand, improvising to win over stakeholders and co-creating new products and markets – are more effective than the scientific approach.

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3.9. Online appendix A:

A model of the entrepreneurial decision-making process

3.9.1. Setup

Entrepreneurs typically start with a business idea, check its feasibility and potential, and make one of the following three alternative decisions: (1) develop the idea, which means that they commit to it by investing resources for its market commercialization; (2) pivot to a new idea, which they need to check for feasibility and potential before they decide whether to commit to its development; (3) close the business if neither of the previous two options yield higher outcomes than their opportunity cost. These search cycles may repeat themselves as shown in Figure 7 in the text. Thus, entrepreneurs may commit to an idea or abandon the business after they pivot more than once. Especially at their initial stage, entrepreneurs face resource limitations, and they consider business ideas sequentially, one at the time. As discussed by Gans et al. (2019), if entrepreneurs do not develop an idea and pivot to a new one, they cannot later on resurrect the idea they abandoned.

During each cycle the entrepreneurs check the feasibility and potential of the idea they came up with at the beginning of the cycle, and at the end of the cycle, or the beginning of the new cycle, when they have to decide whether to commit to the development of the idea, they may come up with a new idea that they compare with the current one. Entrepreneurs check the feasibility and potential of their ideas at a cost borne during the check and feasibility stage. Thus, at the end of a cycle, the check and feasibility cost of the current idea is sunk, while if they pivot to the new idea, they pay the cost to check the feasibility and potential of the new idea. If they commit to develop the current idea, they pay a development cost. If they pivot to a new idea, they do not pay the development cost of the current idea, but they pay the development cost of the new idea at the next cycle, if they decide to develop it. Otherwise, they either abandon the business or start a new cycle by pivoting to a new idea.

Entrepreneurs predict the present value of their business ideas as a random variable v with finite mean and variance, cumulative distribution F, and support $[-a, a]$. Define F_n to be the cumulative distribution of v associated with n^{th} idea generated by the entrepreneurs, with $n \geq 1$. Then, $n = 1$ represents the idea entrepreneurs start with, and any additional $n > 1$ implies that entrepreneurs pivot one or more times. As discussed in the text, over time entrepreneurs acquire information about the idea they check before they make a commitment. This makes the v associated with the n^{th} idea more certain than the v associated with the $(n+1)^{th}$ idea (or any other future idea) that has not yet been checked and studied. We assume that entrepreneurs develop ideas from distributions with the same expected value that represent the characteristics of the entrepreneurs (e.g. ability, experience, education) or the domain in which they operate (e.g. industry, country). We represent the lower uncertainty of the previous idea by assuming that F_n dominates F_{n+1}, in the sense of second-order stochastic dominance, where n+1 is the next idea that pops up, or a new opportunity that is sufficiently different from the current one that it requires that the start-up pivots to some new direction.

Technically, second-order stochastic dominance implies that the n^{th} and $(n+1)^{th}$ ideas have the same expected value, that is, $\int_{-a}^{a} F_n(\omega)\,d\omega = \int_{-a}^{a} F_{n+1}(\omega)\,d\omega$, but $\int_{-b}^{a} F_n(\omega)\,d\omega > \int_{-b}^{a} F_{n+1}(\omega)\,d\omega$, with $b > a$. We also assume that because entrepreneurs explore in the same broad landscape, over time they learn about the distribution from which they draw the ideas they explore. We then assume that the relative uncertainty of the $(n+1)^{th}$ idea compared to the n^{th} idea diminishes as n increases, that is $\int_{-b}^{a} \left(F_n(\omega) - F_{n+1}(\omega)\right)d\omega$ diminishes with n. This assumption is not critical, and as we will see, it only helps to establish that entrepreneurs do not pivot indefinitely, but stop pivoting at some point. #

As discussed in the text, entrepreneurs face an opportunity cost x, and they know that if they develop an idea, they will eventually observe v. Therefore, even if they do not observe v, when they have to make the decision to commit to the development of the idea, they know that they will earn v only if $v \geq x$, otherwise they earn x. We assume it costs 1 to explore each new idea. The expected value V_n of the n^{th} idea is therefore

$$V_n = \int_x^a v\, dF_n(v) + xF_n(x) - n = a - \int_x^a F_n(v)\, dv - n \qquad (1)$$

where the second expression stems from integration by parts.

In order to decide whether to commit to the present idea or pivot to another idea, entrepreneurs predict the value of the idea they can pivot to, which is

$$V_{n+1} = \int_x^a v\, dF_{n+1}(v) + xF_{n+1}(x) - (n+1) = a - \int_x^a F_{n+1}(v)\, dv - (n+1) \qquad (2)$$

Entrepreneurs pivot if

$$V_{n+1} - V_n = \int_x^a \left[F_n(v) - F_{n+1}(v) \right] dv - 1 \geq 0 \qquad (3)$$

Assuming that $-a < x < a$, the expression $\int_x^a \left[F_n(v) - F_{n+1}(v) \right] dv$ is non-negative and declines with n. Therefore, (3) eventually becomes negative, and entrepreneurs stop pivoting when n becomes such that $V_{n+1} - V_n \leq 0$. To characterize the decision to exit, we assume that the full returns of entrepreneurs are $V_n + \xi_n$, where ξ_n is a shock revealed after the entrepreneurs decide whether to pivot. Therefore, the shock does not affect $V_{n+1} - V_n$. However, it affects the decision to exit. When the entrepreneurs commit to the n^{th} idea, they exit if $\xi_n < -$

V_n, otherwise they develop the idea. Since n maximizes V_n, the entrepreneurs could not make a better decision about exit or commitment by picking a different n.

3.9.2. Scientific entrepreneurs

Thanks to theory and tests, the scientific approach affects the prediction of entrepreneurs. We assume that it affects the degree of second-order stochastic dominance of F. As discussed in the text, we have two cases. On the one hand, theory and tests help scientific entrepreneurs to explain more precisely some stochastic factors that they think affect v. This raises the degree of second-order stochastic dominance of F because the stochastic process depends on a subset of the stochastic factors that affect the dominated distribution. On the other hand, theory and tests help scientific entrepreneurs to see new stochastic factors. The scientific approach then produces a dominated distribution, in the second-order stochastic sense, because it reveals more randomness than in the case of the counter-factual non-scientific entrepreneur.

As discussed in the text, we assume that the scientific approach has no effect on the mean of the distribution. This may be an extreme assumption in that the scientific approach may eliminate biases that could generate higher or lower expected values, or it may show where to find better distributions of returns. However, the most important effect of the scientific approach is prediction, and we focus on this. To put it slightly more weakly, our analysis assumes that the effect of this approach is largely on the variability of F, and the effect on the mean is negligible. This is most reasonable if we assume, as we do, that F reflects the characteristics of our entrepreneurs or the landscape in which they search. In this respect, we study a context in which the opportunities of the entrepreneurs are defined, and the question is mostly how entrepreneurs predict the realizations of these opportunities.

Our two cases imply that $\int_x^a F_n(v)\,dv$ could be smaller or larger, according to whether the scientist entrepreneurs believe the phenomenon exhibits higher or lower variability. If the perceived variability is higher, it is easy to see from (1) that, other things being equal, V_n is larger, and vice versa if the perceived variability is lower. As noted, the distributions F_n yield the same mean. However, because we focus on the mean of the distribution when $v \geq x$, we only count the realizations of v in the higher end of its support, which implies a higher mean of the distribution with fatter tails, conditional on $v \geq x$.

Suppose that V_n is the level of n such that entrepreneurs stop pivoting. As discussed in the previous section, entrepreneurs exit if $\xi_n < -V_n$. Then, if entrepreneurs perceive high opportunities at the high end of the distribution (fatter tails), the scientific approach makes them more conservative, lowering the perceived expected value V_n. The scientific entrepreneurs will then be more likely to exit; vice versa if entrepreneurs perceive low opportunities, and the scientific approach raises their confidence that they can reach higher-end results. This implies that the effect of the scientific approach on exit depends on whether entrepreneurs are more likely to underestimate or overestimate opportunities. This leads to Proposition 1 in the text: if there are more overconfident entrepreneurs, we observe on average that the scientific approach raises the share of exits.

We now turn to the effect of the scientific approach on pivot. As discussed earlier, the distribution F_n dominates, in the second-order sense, the new idea that entrepreneurs explore, whose distribution is F_{n+1}. This implies $\int_x^a F_n(v)\,dv \geq \int_x^a F_{n+1}(v)\,dv$. The question is whether the distribution F_{n+1} of the scientist entrepreneurs dominates, in the second-order stochastic sense, the distribution F_{n+1} of the counterfactual non-scientist entrepreneurs. As noted earlier, the scientific approach could affect this distribution in both directions. Scientists may see fewer or more opportunities, which raises or lowers $\int_x^a F_{n+1}(v)\,dv$.

As discussed in the text, we make two reasonable assumptions. The first one is that, whether scientists or non-scientists, unimaginative or confused, entrepreneurs show a less pronounced difference in $x(a)\,F(n)\,dv$ than $x(a)\,F(n+1)\,dv$. There will still be some differences among these entrepreneurs in $x(a)\,F(n)\,dv$, with unimaginative entrepreneurs showing slimmer tails than confused, and scientist entrepreneurs correcting these biases by expanding or contracting the distribution accordingly. However, as discussed in the theory section in the text, the information that has become available about the n^{th} idea, which has just been explored, has levelled the information set of the different entrepreneur types, making their distributions closer. The second assumption is that being unimaginative or confused is a trait of the entrepreneur. Therefore, entrepreneurs predict in unimaginative or confused ways both the current and the next idea. However, because they have less information about the next idea, a confused entrepreneur exhibits a higher positive gap in $x(a)\,(F(n) - F(n+1))\,dv$, which the scientific approach reduces; conversely, an unimaginative entrepreneur exhibits a lower positive gap, which the scientific approach increases.

As a result, from the right-hand side of (3), if the scientific approach makes entrepreneurs less confused, the optimal n of scientist-entrepreneurs lowers compared to the counterfactual non-scientist entrepreneurs, and vice versa if the scientific approach makes the entrepreneurs more imaginative. In turn, this implies that unimaginative non-scientist entrepreneurs exhibit the lowest optimal n, while confused non-scientist entrepreneurs exhibit the highest optimal n. Therefore, the scientific approach reduces the range between high and low numbers of pivots, as stated in Proposition 2 in the text.

Finally, a minimalistic approach suggests that whether scientific entrepreneurs adjust to a distribution closer to the 'true' distribution of the phenomenon is an empirical question. A stronger view suggests instead that if the scientific approach helps to make better predictions, entrepreneurs who adopt this approach enjoy higher performance. As shown in the text, empirically we corroborate this prediction.

3.10. Online appendix B:

Scientific Intensity

To understand if entrepreneurs adopt the scientific approach, and to what extent, we quantify the intensity of the adoption of key four elements (theory, hypotheses, tests, and critical evaluations) in their decision-making process.

To adequately capture different nuances of the adoption of the scientific approach, we first code for the presence of the four elements of the scientific approach (i.e. does the entrepreneur have a theory) and then assign a score to four dimensions for each element of the approach. Each dimension is assigned a score ranging from 1 to 5, where 1 indicates that the entrepreneur displays a low degree of adoption of the scientific approach and 5 indicates that the entrepreneur displays a high degree of adoption of the approach. We therefore code sixteen variables (four dimensions for each of the four elements), since theory, hypotheses, tests and evaluations are complex constructs that include several dimensions, which we detail in the table below. To calculate the variable scientific intensity, we compute the average value of the sixteen variables that measure the adoption of the scientific approach.

Element	**Dimension**	**Description**
Theory: This part of the interview aims to understand if the respondent has a theory, i.e. a cohesive story about the mechanisms underlying the problem and the building blocks that need to be in place for the business to be viable.	*Theory_Clear*	Score to quantify whether the theory is understandable
	Theory_Articulated	Score to quantify if the theory goes into details, i.e. whether the respondent can provide a high level of detail consistent with the main theory
	Theory_Alternatives	Score to quantify if the theory expressed by the respondent considers additional aspects not currently implemented by the company, but that could be implemented
	Theory_Evidence	Score to quantify if the theory is supported by data. Data could be industry reports or information gathered by the respondent itself

Element	Dimension	Description
Hypotheses: This part of the interview aims to understand if the respondent has identified specific hypotheses based on their theory, i.e. propositions that logically flow from the theory but that have yet to be tested.	*Hypothesis_Explicit*	Score to quantify if the respondent can clearly articulate the fundamental hypotheses that make his/her business viable
	Hypothesis_Coherent	Score to quantify if the hypotheses are coherent with the theory elaborated earlier
	Hypothesis_Detailed	Score to quantify if the respondent is able to tell what he/she wants to learn in clear and concise terms
	Hypothesis_Falsifiable	Score to quantify if hypotheses are formulated in a way that allows the respondent to support it or refute it through tests

Element	**Dimension**	**Description**
Testing: This part of the interview aims to understand if the respondent has tested their hypotheses based on their theory.	*Test_Coherent*	Score to quantify if the objective of the test is in line/coherent with the hypotheses expressed earlier
	Test_Valid	Score to quantify if the test measures what it is intended to measure
	Test_Representative	Score to quantify if the test uses a representative sample that accurately reflects the characteristics of the broader group targeted by the respondent
	Test_Rigorous	Score to quantify if respondents use the right type of test and with the right procedures

Element	Dimension	Description
Evaluation: This part of the interview aims to understand if the respondent has analyzed the data collected and whether he/she is actually making use of their findings.	*Val_Data*	Score to quantify if the evaluation is based on objective data – as opposed to making an assessment based on subjective perception
	Val_Measure	Score to quantify if the key measures used in the evaluation are consistent with what respondents identified as their priorities in the earlier questions
	Val_Sistematic	Score to quantify whether the collection and analysis process are well-organized and systematic
	Val_Explanatory	Score to quantify if the respondent has clarity on the main findings of the tests and their implications for the business – e.g. what to do based on the findings

4

The Way You See the Problem, Is the Problem: Exploring the Role of Experimentation within a Hackathon

(Joint with Shanming Liu and Danilo Messinese)

4.1 Introduction

The notoriously low survival rate of start-ups has urged scholars to examine why new start-ups fail. One key argument is that business ideas generated by entrepreneurial teams often exhibit poor product-market fit that are ultimately bound to fail (Kirsch and Goldfarb, 2006). Another stream of research suggests that new businesses fail because teams are not able to successfully implement ideas (Chandler and Lyon, 2001). While teams create about one third of all start-ups (Aldrich et al., 2017) and evidence suggests that team based start-ups are much more likely to survive and grow than solo-founder start-ups, we lack an understanding of the factors that sustain creativity and innovation within entrepreneurial teams. Following Aldrich et al., (2017), we speculate that the low survival rate of start-ups could stem, at least in part, from limits to creative and innovative action of entrepreneurial teams generated by the team's starting conditions.

The key question this study is trying to address is: How can founding teams select and generate good business ideas? More specifically: Would they be able to generate more novel business ideas if they were to search more broadly? With this study we are particularly interested in examining the dynamics of the creative process within entrepreneurial teams as they work to identify a suitable business idea for their start-up. While previous research has shown that entrepreneurial teams can benefit from diversity (Eisenhardt and Schoonhoven, 1990; Gray, 2017), research in this area has consistently shown that most founding teams are highly homogenous (Ruef et al., 2003; Ruef, 2010). As a result, the initial homogeneity within an entrepreneurial team can potentially limit access to heterogenous information sources and constrain the range of viewpoints and business ideas that can be generated. This is likely to hurt creative performance, which is typically observed in the initial stages of new venture foundation, when entrepreneurial teams are attempting to identify a viable business idea. In bringing together insights from literature on creativity and early-stage entrepreneurship, we are looking to gain a better understanding of what helps entrepreneurs generating and selecting viable business ideas.

In order to gather causal evidence in a realistic setting, we are planning to conduct a field experiment embedded within a hackathon. Hackathons are short events that gather a crowd of aspiring entrepreneurs, makers and enthusiasts who work in teams to identify solutions for various types of problems. In our hackathon, we will recruit teams of potential entrepreneurs who will work on a predefined task for one day. We intend to use this opportunity to randomly assign half of the teams to a treatment condition where teams are nudged to search in a broader space vis-à-vis a control condition where teams are free to search for ideas without guidance. We expect that the random allocation of a broader search space will have an impact on both idea generation and idea selection. In particular, we expect treated teams to generate less ideas, but to select more novel business ideas. The consideration that teams tend to spontaneously search quite narrowly stems from both practical observations and theory – findings in organizational behaviour, strategy and management find that teams under conditions of low diversity tend to search narrowly.

This paper makes also an important methodological contribution in combining a field experiment with text analysis techniques. We are, in fact, going to use recording devices to have transcripts of the conversations each team is going to produce during the event. This will allow us to unpack the dynamics of team work and provide novel measures of idea novelty. We see several potential contributions stemming from this work. On the one hand, we introduce a new perspective on a literature predominantly focused on the role of proximity on creativity. On the other hand, with this setting, we overcome difficulties in measuring and observing team dynamics, especially in the context of early stage entrepreneurship, aspect that has hindered empirical work in this area. If we were to find that entrepreneurs might benefit from a broader search space, this could have important implications for practitioners as well. We can easily imagine accelerators, incubators and mentors leveraging these findings to develop effective coaching techniques.

4.2 Theoretical background

In developing our argument that entrepreneurial teams can benefit from a broader search space to challenge their initial and collective beliefs and assumptions, we build on literature on early stage entrepreneurship and creativity. Research on team-based creativity shows that groups face different challenges than solo creators. A well-known issue in this regards is groupthink (Janis, 1982), which consists in irrational or dysfunctional outcomes as a consequence of collective decisions that aim to preserve harmony or conformity within groups. Research in this area (Sunstein and Hastie, 2015) has identified two key mechanisms that foster groupthink: informational signals and reputational pressures. Information signals are clues that individuals use to feel they are part of an ingroup. Information signals often generate ‘cascades effect’ where groups tend to follow the statements of those who speak first. Reputational pressure, instead, means that individuals tend to conform to what the rest of the group says, in order to avoid disapproval. This often results in groups not correcting the errors of their members, but rather to amplify them. Another intended consequence of reputational pressure is that groups may focus on what everyone already knows and agrees on. Consistently, researchers on team creativity have looked to identify suitable remedies to at least alleviate these issues.

In a 2010 article by Girotra, Terwiesch, and Ulrich on idea generation and the quality of best ideas, the authors focus on group structures that are more beneficial for creative tasks. The authors find that it is more beneficial for teams to work independently at first and only subsequently work together. This finding goes against the grains of frequently recommended brainstorming techniques that suggest building on each other ideas while working together. While Girotra et al. (2010) suggest that working individually prior to working in a group can counterbalance the negative consequences of groupthink, other researchers have focused on the role of diversity. Farley and Farr (2010), for instance, conduct a survey and find that task conflict has a curvilinear effect on team creativity and introduce the idea that task conflict can be beneficial at different stages of the creativity process. Kurtzberg and Amabile (2010) examine the specific group processes and dynamics that affect the levels of creative production within teams and find consistently with other studies that diversity helps the creative process. Finally, Hoever et al. (2012) find that diverse teams perform more creatively than homogenous teams when they engage in perspective taking.

Both the entrepreneurship and creativity literature divide the creative process team go through in two different phases: idea generation and idea selection. This distinction, however, has been generally overlooked in the entrepreneurship literature. A notable exception is the study by Perry-Smith and Coff (2011) that focuses on the effect of mood for generating and selecting ideas for new ventures. In particular, the authors borrow from the creativity literature to show that the idea generation and idea selection phase of the creative process are quite different and for this reason can benefit from different moods within the team. Overall, there is growing consensus that entrepreneurship is a process and it is largely iterative in nature, therefore feedback and team interactions play a critical role. This is also evident in recent studies in entrepreneurship that focus on the role of information gathering and assessment by entrepreneurs and their role for developing business ideas (Camuffo et al., 2018 Chatterji et al., 2017; Leatherbee and Katila, 2017). Moreover, clearly framing problems and generating alternatives has been shown to counterbalance the negative effect of assumptions and pre-existing beliefs entrepreneurs might have.

While there is overall consensus that introducing diversity, and potentially even conflict, can be beneficial for team performance, two aspects remain unclear. Firstly, what are the mechanisms resulting in better outcomes in the idea generation and in the idea selection phase of the creativity process? Secondly, it remains unclear how to make sure that the diversity of viewpoints leads to beneficial outcomes. In answering these questions, we borrow a technique called moon-shot thinking, that has been used by Google in the last few years. When using moon-shot thinking, all individuals within a team are encouraged to go after big questions and find solutions that can work on a large scale. We argue that using a similar technique – that provides a broad search space - can lead to the formulation of novel ideas. The rationale is that team members are given a specific reference point that helps them avoid the social pressure that comes from rejecting the group's dominant position because they can use the common goal as an objective reason to select low-quality ideas.

At the same time, we expect this technique to have different effects depending on the phase of the creative process entrepreneurial teams are dealing with. Firstly, we expect that moon-shot thinking can contribute to generating less ideas, but these ideas will be of higher quality. The rationale being that challenging groupthink can lead to generating less ideas because one team member is questioning the validity of these ideas. This is also likely to result in ideas that are of higher quality, because team members have been encouraged to carefully think about the limitations of their ideas. With regards to idea selection, instead, we expect moon-shot thinking to result in a selection of ideas that are more novel, but less feasible. This is due to the fact that introducing a wider search space is likely to lead team members to choose very novel ideas, that tend to be harder to implement. In line with these arguments, we propose the following two hypotheses:

H1: *Moon-shot thinking in the idea generation phase will result in groups generating less ideas, but these ideas will be of higher quality.*

H2: *Moon-short thinking in the idea selection phase will result in groups generating more novel, but less feasible ideas.*

4.2.1 Experimental design

It would be extremely difficult to collect observational data on early-stage entrepreneurial teams engaging in the process of idea generation or selection. Even if we were able to do so, there would be several confounding effects that represent threats to causal identification. Conducting surveys on this topic would also be challenging, and likely to result in biased responses, as teams would have to retrospectively recollect what they did and might not be effectively able to identify bottlenecks and issues in the process of idea generation. For these reasons, we will test our hypotheses using an experimental research design that will allow us to identify and estimate the causal effect of introducing red teaming in early-stage entrepreneurial teams.

We plan to embed a field experiment in a hackathon by randomly assigning entrepreneurial teams to either a treatment (moon-shot thinking) or a control (no moon-shot thinking) conditions. A Hackathon represents a suitable setting to test our hypotheses because it brings together groups that are working together to identify suitable business ideas. While the first hackathons were held in 1999 and involved coders, these events have gained popularity in the last couple of decades. Hackathons have moved beyond the developers/coders community and, as a consequence, they now span a wide range of industries and sectors ranging from public defence to food, design, and fashion. What all hackathons have in common is that they involve teamwork to generate business ideas or solutions to problems. Therefore, this represents a suitable setting to examine how early stage entrepreneurs decide what to do as they undergo the process of idea generation and selection.

Given the heterogeneity of events that are classified as hackathons, we intend to run a hackathon specifically targeting aspiring entrepreneurs who have yet to identify a business idea, but have the desire to start a business. We are therefore going to encourage and attract the participation of qualified and motivated aspiring entrepreneurs in two ways. Firstly, the hackathon is going to be marketed using information sources that are typically used by early stage aspiring entrepreneurs. These will include social media, online platforms, traditional press, and word of mouth. Secondly, we are also going to advertise that the hackathon will provide in-kind prizes (such as mentoring, co-working space, legal support, etc.) that will help entrepreneurs further developing their ideas after the hackathon.

We plan to collect a number of variables for the baseline survey including detailed information about each member of the team. These details will include demographic information such as age, gender, education, but will also collect information about attributes associated with creative outputs, including divergent thinking ability, self-confidence, diverse expertise, and a problem-finding orientation. We will use this information to randomly allocate teams to either a treatment or a control condition.

In addition, we will collect data using audio recording techniques developed through Open Badge (Lederman et al., 2017). Open Badge is a device invented at MIT that records conversations while providing real-time information about the extent to which team members share information and the tone of the conversation. In this way, we will be able to gather detailed data about participants' interactions within the team, and thus measure whether teams are contributing equally to the idea generation process or not, and whether the introduction of a wider search space changes dynamics within teams. This could potentially help us identifying key mechanisms. We will also administer a survey at the end of our intervention.

Our hackathon will focus on teams working on the same broad task. We are currently advertising the hackathon as a generic event for aspiring entrepreneurs that want to use technology to improve the future – they will discover the exact topic when the hackathon starts. The rationale is that advertising a precise topic (such as fashion, for instance) might draw a crowd of individuals who already have generate ideas in this area, and might just want to pitch their idea in front of investors at the end of the event. This is a commonly observed issue in some hackathons, and we therefore decided to keep the topic wide during the recruitment phase. During the hackathon, all teams will be engaged in some activities to generate business ideas related to the topic chosen for the event. The content and length of the hackathon is going to be the same for both groups. We will also take a number of measures to ensure the internal validity of this experiment. We will avoid contamination between treated and control teams by assigning them to different locations in the same building. However, they will work on separate floors. It is very unlikely the teams will meet and discuss key elements of the treatment because the treatment will consist in a subtle nudge sent discretely to each team participating to the hackathon. In addition, a team of research assistants will overcome the event and check that no contamination occurs. We will also make sure that several environmental conditions are kept constant including light noise and temperature, which have been shown to actually affect group productivity.

4.2.2 Measures

We are interested in measuring several dependent variables, as detailed below.

Idea generation: In the idea generation phase, we are going to measure the number of ideas that are generated by the team, but we are also interested in qualitative measure of these ideas. We will use established measures from the creativity literature such as novelty and usefulness, but we also add an assessment of the market potential and flexibility.

Idea selection: In the idea selection stage, we will also focus on novelty, usefulness, market potential and feasibility.

It is particularly difficult to measure the novelty and usefulness of new ideas, and for this reason we decide to triangulate and measure these variables in different ways. One way will be to use Amabile technique (1996), which uses the consensual assessment technique where audience members will independently rate the ideas that will be presented to them. Three raters will independently score all the submissions included in the study. We will use a Likert scale (1 = ‘‘Strongly Disagree’’ to 7 = ‘‘Strongly Agree’’), to rate each idea on the item ‘‘This idea seems novel,’’ with novelty defined as the degree to which the content of the idea seems different from existing ideas (Ford, 1996; Csikszentmihalyi, 1999). Following Berg (2016) the order of the ideas will be randomized for each rater, and the raters will be asked to read 10 ideas before they start rating to establish a means of comparison. We will check for inter-rater reliability and agreement. Secondly, we will analyse the transcripts of the conversations among members of the same team using text-based techniques. Through these techniques, we will detect if treated entrepreneurs discuss more or less topic, and what is the sentiment that prevails during their conversation. Finally, we will have a panel of twelve judges who will rate ideas based on pre-defined criteria to measure the novelty and feasibility of the ideas presented by the entrepreneurs at the end of the event.

4.3 Conclusion

This study aims to examine the impact of moon-shot thinking on the idea generation process. By embedding a field experiment within a hackathon, we will be able to observe teams of aspiring entrepreneurs and the dynamics of the process of business idea generation. While we are currently recruiting participants for the experiment that we expect to run in November 2019, we envision the following contributions. Firstly, this study can potentially contribute to literature on early stage entrepreneurship and creativity. Secondly, findings from this experiment can contribute to the current conversation on the role of feedback and mentoring for the development of entrepreneurial teams (Chatterji et al, 2017). This is an important aspect to explore given the growing consensus on the largely iterative nature of the entrepreneurial process.

By using a novel setting, we will be able to observe dynamics that unfold within a team in a relatively short amount of time. However, the big advantage of this setting is that it allow to observe aspiring entrepreneurs using a realistic setting, while running a randomized controlled trial. Finally, we are aware that this study will be subject to several limitations, external validity being an important one. However, this project has the potential to open up avenues for further research on creativity and entrepreneurial teams in new ventures, which largely outweighs its limitations.

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